ChatGPT

MemoryLink – 30-Day MVP Plan (Local-First Personal Memory Layer)

Introduction and Overview

MemoryLink (working title) is a **local-first, secure personal memory system** designed to bridge multiple AI agents and developer tools with a shared long-term memory. Today, AI assistants and IDE integrations lack a persistent context – each operates in a silo with no memory of what others did. MemoryLink solves this by providing a **unified memory layer** that any agent or IDE can plug into via a simple API. The result is a “personal knowledge vault” that remembers user preferences, past interactions, and important context across sessions and tools, all while keeping data on the user’s device by default for privacy.

This document outlines a comprehensive plan for a 30-day Minimum Viable Product (MVP) of MemoryLink. It covers the project’s **objectives, scope, functional and non-functional requirements, architecture scaffolding, implementation approach,** and how we will incorporate **gamification** into the developer experience. The goal is to deliver a working prototype that internal teams can use on their laptops via Docker (with an eye toward later deployment on Kubernetes), demonstrating the core value of a **crisp hybrid local/cloud boundary** and an easy-to-integrate memory API.

Goals and Objectives

- **Persistent Shared Memory:** Enable AI agents, chatbots, and developer tools to **store and retrieve context** from a shared memory service, preventing loss of context between sessions or across different tools [1] [2]. This elevates AI workflows from stateless prompts to continuous, context-rich interactions.
- **Local-First Privacy:** Prioritize a **local-first architecture** where all personal data and memory are stored **on the user’s device by default** (offline support), with optional encrypted sync for collaboration or backup [3]. Users retain control of their data, ensuring sensitive information isn’t sent to cloud services without consent.
- **Secure Personal Vault:** Implement strong **encryption** and access control so that the personal memory store is private and secure. Even if data is persisted or synced, it should be encrypted at rest (using keys controlled by the user) to protect confidentiality [4].
- **Standard Integration Interface:** Provide a **“boring and stable” API** that adheres to common standards (e.g. simple REST endpoints) so that **any agent or IDE can integrate without custom glue**. By using an open protocol for memory (inspired by the Model Context Protocol, MCP), MemoryLink’s API will be immediately familiar and easy to adopt [5].
- **Developer-Friendly UX:** Deliver a delightful developer experience, including **clear documentation** and a novel **gamified onboarding**. Setting up, using, and extending MemoryLink should be engaging – internal developers will be guided through installation and usage via CLI/Makefile-driven “quests” that encourage discovery and learning.
- **Deployment Readiness:** Ensure the solution runs reliably in Docker containers for development laptops (primary target for the MVP), and lay the groundwork for eventual deployment to

Kubernetes in later phases. This includes providing Docker Compose for easy local setup, and designing stateless or easily containerized components that can scale out.

Scope of the 30-Day MVP

The MVP will focus on delivering the **core functionality** of MemoryLink within a 30-day timeline, sufficient for internal teams to start using and providing feedback. Below is what's **in scope** for the MVP, as well as what's **out of scope** (to be addressed in future iterations):

- **In Scope (MVP Features):**
- **Memory Storage & Retrieval API:** A local service exposing RESTful endpoints to **add** pieces of memory (text with associated metadata) and **search** for relevant memories. For example, endpoints like `/add_memory` and `/search_memory` will allow clients to store conversation snippets or notes, and retrieve them later via semantic or keyword queries [5].
- **Vector Search Engine:** Integration with a lightweight **vector database or embedding store** (running locally, e.g. via a container) to enable semantic search. This allows the memory to be queried by meaning, not just exact keywords, so that AI agents can retrieve relevant context even if wording differs.
- **Metadata and Indexing:** Store essential metadata with each memory entry (e.g. timestamps, tags, source/tool info, user/session identifiers) in a structured form (e.g. a local SQLite or lightweight database). This enables filtered queries (such as "get last 5 entries tagged #meeting") and future multi-user or team scope isolation.
- **Local Encryption:** Implement basic **encryption at rest** for the stored memory data. For MVP, this could mean encrypting the content fields in the database using a symmetric key. The key might be provided via environment variable or user passphrase on startup. This ensures that even if the local database or files are accessed directly, the personal memories remain unreadable without the key [4].
- **Single-User Personal Vault:** The MVP will treat the entire memory store as a single user's personal vault (sufficient for an individual developer or a single "internal team" context). Multi-user or team-collaboration features (like sharing memory between users or across an org) will be considered out-of-scope for MVP.
- **Command-Line Interface (CLI):** A simple CLI tool or set of Makefile commands to interact with the memory service (for setup and basic usage). For example, a developer can run `make run` to start the server, `make add_sample` to add a test memory, or `make query` to perform a sample search. This is both for testing the API easily and for gamified onboarding.
- **Documentation with Gamification:** Documentation (in English) will be provided, focusing on quick start guides for internal teams. The docs will incorporate a **gamified tutorial** – for instance, a "treasure hunt" where developers follow clues by running provided CLI commands or Makefile targets to learn features. This is in scope as part of making the MVP engaging and internally adopted.
- **Dockerized Deployment (Local):** Delivery of a Docker Compose configuration that sets up the MemoryLink service and any supporting components (e.g. a vector DB) on a developer's laptop with minimal effort. Running `docker-compose up` should launch the system locally. This ensures everyone can easily run the MVP in a consistent environment.

- **Basic Test Suite:** A minimal set of tests (unit and integration tests) to verify core functionalities (e.g., adding and retrieving memory, encryption working, API responding). This ensures the MVP is reliable and prevents regressions during rapid iteration.

- **Out of Scope (Post-MVP):**

- **Cloud Sync & Multi-Device:** Any form of cloud-based synchronization or multi-device data sharing is deferred. While the design will keep a “crisp boundary” between local and cloud (so it can be added later without rearchitecting), the MVP will function **offline-first** with data on local disk only [3] .
- **Team/Org Multi-User Features:** The MVP won’t include multi-user account management, sharing memories between accounts, or complex permission systems. All memory data is assumed accessible to the single user (though still protected from external access by encryption and local storage).
- **Advanced Memory Management:** Features like automated summarization of old memories, memory expiration/decay policies, or rich query languages will be noted as future enhancements. MVP will rely on basic CRUD and search operations (with possibly simple tagging and manual cleanup).
- **Rich User Interface:** Aside from the CLI and possibly a very simple web dashboard for inspecting memory (if time permits, e.g. a basic web page showing recent memories), no polished GUI is planned. The primary consumers in MVP are other tools and agents via API, and developers via CLI/Makefile.
- **Kubernetes Deployment:** While we will prepare the app in a way that it *can* be containerized and later moved to Kubernetes (e.g. by avoiding stateful single-instance assumptions, externalizing configs), we will not deliver a full Kubernetes helm chart or deployment in 30 days. That will be a next-phase task once the MVP is validated on laptops.
- **Extensive Integrations:** We will not write dedicated plugins for IDEs or bots in the MVP. Instead, we ensure the API is easy to call so that integration is trivial. (For example, we won’t build a VSCode extension in 30 days, but we will document how one *could* call the API from VSCode or other tools.)

By keeping the MVP scope focused on the **core memory service and its immediate usability** by developers, we ensure we can deliver a working solution in 30 days that demonstrates value and gathers feedback for the next iteration.

Functional Requirements

The following are the key functional requirements for MemoryLink’s MVP, detailing what the system must do. Each requirement corresponds to a capability that directly supports the objectives of the project:

1. **Memory Ingestion (Add Memory):** The system shall allow clients to **add new memory entries** via a simple API call. An **entry** consists of a piece of content (e.g. a text snippet such as a conversation message, summary, note, or code fragment) plus relevant metadata:
2. **API Endpoint:** `POST /add_memory` (accepting JSON payload with content and metadata). For example, a payload might include `{ "text": "...", "tags": ["meeting","projectX"], "timestamp": "...", "user": "alice" }`. On success, the entry is stored and an ID is returned.

3. **Metadata Handling:** At minimum, the system will tag each memory with a timestamp and an origin or session ID if provided. It may also accept optional tags or categories from the client. This metadata will be saved in a structured form (relational DB or key-value store) for filtering.
4. **Vector Embedding Indexing:** Upon ingestion, the text content of the memory will be converted to a vector embedding (using a chosen language model or embedding model) and stored in a vector index for similarity search. This enables semantic recall of the memory later. The embedding computation might use a small local model or an API like OpenAI if available, but preference is to use a lightweight local model for privacy (if feasible within MVP constraints).

5. **Encryption on Write:** If encryption is enabled, the plaintext content will be encrypted before storing in the database (or the database file itself is on an encrypted volume). For MVP, a symmetric encryption (e.g. AES) with a static key can wrap the content field. This ensures the stored memory content is not readable in plain form without the key.

6. **Memory Retrieval (Search Query):** The system shall allow clients to **query the memory store** and retrieve relevant entries:

7. **API Endpoint:** `GET /search_memory` (with query parameters or JSON body specifying search criteria). Two primary forms of query will be supported in MVP:
    - **Semantic Search:** A query string (natural language or keywords). The system finds top-N similar entries by embedding similarity. For example, a query “what was decided about API versioning?” should return memory items related to API decisions, even if exact words differ.
    - **Metadata/Keyword Filter:** Optional parameters like tags or time range can be provided to narrow the search. E.g., `GET /search_memory?tag=meeting&since=2023-01-01`.
8. **Results:** The service returns a list of memory entries (or references to them) sorted by relevance score. Each result includes the stored text (decrypted on the fly if encrypted at rest) and its metadata (timestamp, tags).
9. **Relevance and Ranking:** The vector search component handles similarity scoring. If a keyword filter is provided, the system will first filter by metadata (e.g., only memories tagged “meeting”) then within those perform similarity ranking or direct keyword match. In MVP, we’ll focus on semantic similarity as the main retrieval mechanism for flexibility [6] (neural search to find content without exact keywords).

10. **Performance:** The search should be reasonably fast for the expected MVP dataset (which for an individual’s memory might be on the order of hundreds or a few thousand entries). Using an efficient vector index (like Faiss or an out-of-the-box vector DB) will ensure low-latency queries.

11. **Standardized API (MCP Compliance):** The design of add/search (and optionally delete) endpoints will follow a standardized pattern so that **no custom integration logic is needed for different tools**. We aim to align with the emerging *Model Context Protocol (MCP)* conventions [5] :

12. The API methods will be **stateless HTTP calls** with JSON payloads, making them tool-agnostic. For instance, any environment that can make HTTP requests (an IDE plugin, a Slack bot, a Python script, etc.) can use the API out-of-the-box.
13. We will include in the documentation an **API schema** or OpenAPI spec to make it clear and potentially allow auto-generation of client SDKs for different languages.

14. **No Bespoke Glue:** Because the API is simple (e.g., an IDE plugin just needs to call `POST /add_memory` whenever the user triggers a save action, etc.), each tool's integration becomes a small configuration or script rather than needing a custom memory solution. This fulfills the requirement that every agent/IDE can plug in easily without bespoke glue code.

15. **Identity and Scope Management:** Even though multi-user support is limited in MVP, the system will enforce a basic notion of **scope**:

16. **Personal User Scope:** Since MVP is effectively single-user (e.g., one developer's personal memory vault), all data is under that user's scope. However, we will architect the data model to allow adding a `user_id` field on entries (and in API calls) so that in future, multiple users or an org-wide memory could be segregated. In MVP this may default to a single user or be configurable via an environment variable.
17. **Session or Context Tags:** The API may allow a client to specify a session/context identifier when adding a memory. This could be as simple as a tag, like `session:planning_meeting_123`. It's not full session management, but it lets clients indicate grouping of memories. The retrieval API can then filter or rank by session if needed (e.g., allow queries like "only search within this session context" in the future).

18. **Permissions:** All memory operations in MVP assume the caller is authorized (since it's running locally for one user). In a later version, authentication tokens might be required for remote or multi-tenant deployments. We note this but do not implement complex ACL in MVP, beyond possibly a basic API key for the service if needed for security when exposed beyond localhost.

19. **Data Security and Privacy:** Security is a first-class requirement, so MVP will implement:

20. **Encryption at Rest:** As noted, memory content is encrypted when stored. The **encryption key management** for MVP will be straightforward: e.g., use a key derived from a passphrase or stored in a config file. The design leaves room for later incorporating user-provided keys or hardware keystores. This meets the privacy goal that even infrastructure or cloud operators can't read personal data if the memory store is moved or backed up [4].
21. **Controlled Sync (Opt-In):** By default, the system does **not send any data off the local machine**. If the user opts in to a future sync feature, only then would data leave the device (and even then, it should remain encrypted with user-controlled keys). For MVP, we simply won't sync, but we will document that *all content stays local unless explicitly shared*, similar to how other local-first tools operate [7] [8].
22. **Auditability:** The system will log memory operations (add/search) to a local log for transparency (e.g., for debugging or future audit). This log will not include sensitive content in plain text if content is encrypted (to avoid leaking secrets via logs). But it can record that user X added a memory at time Y with tags Z, etc. Internal teams can use this to trace how the system is used or debug issues.

23. **Stability and Reliability:** The API should handle edge cases gracefully (e.g., searching with no memories stored returns empty list, adding an overly large memory might be rejected or truncated with warning, etc.). Error responses will be clean and documented (using standard HTTP status codes and messages).

24. **Development & Operational Features:** Since this is an internal-facing MVP, certain features are aimed at developers who will run and maintain the system:

25. **Docker Support:** The service will come with a `Dockerfile` and a `docker-compose.yml` for easy setup. Running the memory server inside a container ensures consistent environment (dependencies, Python/Node version, etc.) across all dev laptops. Docker Compose will also include any supporting service (for example, a container for the vector DB or a Postgres instance if used for metadata).
26. **Configuration via Env/Files:** The system's configurable parameters (like encryption key, storage file paths, port, etc.) will be set via environment variables or a config file. This makes it 12-factor compliant and easy to adjust for different environments (local vs production). For example, `MEMORYLINK_ENCRYPTION_KEY`, `MEMORYLINK_DATA_PATH`, `MEMORYLINK_VECTOR_DB_URL` might be used.
27. **Logging & Monitoring:** Basic logging to console (and optionally to a file) will be included. If running in Docker, logs will go to stdout for `docker logs` access. We might also include a health-check endpoint (e.g. `/healthz`) so that orchestration tools or a load balancer can verify the service is up – useful later when moving to Kubernetes.

28. **Testing Hooks:** Provide some sample data or an easy way to populate with dummy memories for testing. For example, a Makefile target or script can insert a few example memory entries (like sample conversation notes) so that a new user can immediately try a search query and see results. This helps internal teams verify the setup quickly.

29. **Gamified Onboarding and Documentation:** A unique requirement is to make the **learning curve enjoyable**. The following sub-features will address this:

30. **Interactive Setup Guide:** The README or documentation will narrate a story or step-by-step challenge. For example: *"Level 1: Boot up your MemoryLink server. Hint: Try* `make start`*."* When the user runs `make start`, the Makefile will not only start the Docker Compose stack but could also print a success message like *" Mission accomplished: MemoryLink is now running on localhost:8080!"*. The documentation will then present *"Level 2"* which might be adding a memory, and so on.
31. **Makefile Targets as Quests:** We will implement convenient CLI commands via a Makefile (or a small shell script) that corresponds to common tasks:
    - `make start` – Launch the application (Docker Compose up). On completion, it echoes next instructions.
    - `make test_search` – A target that perhaps calls the search API (via curl or a small Python script) and prints sample output, simulating an in-game "challenge result".
    - `make cleanup` – Stop containers and optionally clear data (with an "Are you sure?" prompt styled as a game warning about losing progress).
    - Each of these commands will include some playful messaging. For instance, after adding a memory, the CLI might output: *"You've added your first memory! (Achievement unlocked: Memorizer Level 1)"*, purely for fun.
32. **Progressive Disclosure of Features:** The documentation will be structured so that users discover features gradually, almost like unlocking new tools in a game. For example, after mastering basic add/search, the docs might present an "advanced challenge" to manually inspect the encrypted database or to integrate MemoryLink with a simple Python script, thus encouraging deeper exploration.

33. **Internal Leaderboard (stretch goal):** If time permits, we could have an internal leaderboard or tracking of who in the team has completed the "MemoryLink onboarding quest" (this could be as simple as encouraging them to post a Slack message or the final "flag" output when they finish all steps). While not a core product feature, this can spur friendly competition in learning the tool.
34. These gamification elements in documentation aim to increase engagement, making it more likely that internal developers will not only set up the MVP but also understand its capabilities and think of creative ways to use it in their workflows. It transforms setup and usage from a chore into a fun, memorable experience.

Each functional requirement above will be implemented with the 30-day time constraint in mind, favoring simplicity and using existing libraries or services where possible. The focus is on delivering the **essential capabilities** (memory add/search, local security, stable API) in a usable form.

Non-Functional Requirements

Beyond the core features, MemoryLink must meet several non-functional criteria that ensure the system is usable, performant, and maintainable in a real-world (internal team) setting:

- **Privacy & Security:** As a guiding principle, the MVP must *not compromise user data*. All personal memory data stays on the user's machine unless explicitly shared. By default, the system works offline and does not depend on any external cloud service [7]. Encryption of data at rest is required for privacy, as noted. Additionally, we'll ensure that if the system is accessed via a network, it can be optionally secured (for example, binding to `localhost` only for now, so it's not accessible remotely, or requiring an API token in requests if enabled).
- **Performance and Efficiency:** For an MVP running on a developer laptop, performance needs are modest but important:
- The system should handle **concurrent requests** reasonably (e.g., if an IDE and a chat agent both query at once). We will likely use an asynchronous web framework or run a few worker threads to handle multiple requests.
- Typical operations (adding a memory, searching) should complete within a short time (ideally **< 500ms** for search on a few hundred entries, excluding any large embedding computation). Ingest (add) might involve computing an embedding which could take longer (depending on model), but we will choose a fast model or allow using a remote API as fallback, to keep it within a second or two at most.
- The application's memory and CPU footprint should be light enough to run alongside developer tools. We target using at most a few hundred MB of RAM (including the vector index) and minimal CPU when idle. Embedding generation could be the heaviest operation; we might restrict the size of input or use efficient models to avoid lag.
- **Scalability (Design for the Future):** While MVP will likely handle a single user's data on one machine, we should design with **scalability in mind**:
- Components like the vector store and API service should be loosely coupled so they can be scaled out or replaced. For example, use an interface for vector search so that today it might use an in-process library, but tomorrow it could point to a distributed vector DB cluster without changing the API.
- Stateless API: The API service itself will be stateless (not storing session info in-memory between requests). State lies in the databases. This means the API container can be replicated or moved to Kubernetes easily when needed.

- We plan the data schema such that moving from single-user to multi-user, or single-node to cluster, won't require a complete overhaul. For instance, including a `user_id` field now (even if just one value) avoids adding it later and migrating all data.
- **Maintainability & Extensibility:** Since internal teams will likely contribute to or modify this project, the code needs to be clean and well-structured:
- We will scaffold the project with a clear modular structure (see **Architecture & Scaffolding** section) to separate concerns (API logic, data storage, embedding logic, etc.). This modularity ensures new features (like adding a new type of memory or a new retrieval algorithm) can be done in isolation.
- The code will be documented with comments where non-obvious. Also, we'll include a developer guide in the docs for how to extend the system (for example, how to plug in a different vector DB, or how to add a new API endpoint for a new memory operation).
- Use of standard frameworks and "boring" technology: We'll choose mature libraries (for web server, database, etc.) to avoid spending time on undebugged tech. This also means future developers are likely already familiar with them. Keeping "API adapters boring and stable" is not just for external integrations but also internally – straightforward REST/HTTP and standard libraries make maintenance easier.
- **Reliability and Fault Tolerance:** The MVP should handle common failure scenarios gracefully:
- If the vector search component fails or is unavailable, the API might still allow a basic keyword search as a fallback (so that the system isn't completely down). Or at least, it should return a clear error to the client rather than hanging.
- Startup and shutdown should be clean – e.g., on startup, if the database files or indexes are corrupted, the service might recreate or alert the user, rather than just crash. On shutdown, ensure data is flushed to disk.
- In Docker environment, the containers should restart on failure (we can set `restart: always` for critical containers in Docker Compose). This way, if something unexpected happens, the service will come back up automatically for the user.
- **Compatibility:** Since internal team members may use different OS (Windows, macOS, Linux laptops), the Docker-based approach should abstract those differences. We need to ensure everything we use (like any local binary for vector DB) works across platforms or is encapsulated in a container image. Additionally, the system should not assume GPU availability (use CPU inference for embeddings by default, with an option for GPU if available).
- **Compliance and Data Handling:** If the personal data might include sensitive company info (since internal teams will use it), we should note compliance implications. Because data stays local, things like GDPR or internal data policies are easier to meet (no centralized data store of personal data). If any cloud sync were enabled in future, we'd have to ensure encryption keys are user-held to maintain zero-knowledge of content by the service [4] . MVP will simply avoid holding any centralized data.
- **Internationalization (I18N):** Not a priority for MVP (docs and interface in English), but we should avoid hard-coding content that would make future localization difficult. For now, all documentation and responses will be in English (the primary language for our internal teams).
- **Monitoring & Analytics:** Since this is internal and MVP, we won't integrate heavy monitoring. However, to facilitate debugging, we might include an **optional debug mode** (verbose logging) that developers can turn on. In future, we might add metrics (like number of searches, memory usage) to see how it's used, but not in MVP unless time permits a simple stats endpoint.
- **Gamification Balance:** The gamified elements should remain optional or at least not interfere with power users. A developer who just wants to set up quickly should be able to do so by reading a quickstart section or running `docker-compose up` directly. The gamified guide is an

enhancement for engagement, but the system is fully usable without it. In other words, fun messaging will never obscure important info or make the setup convoluted – it's a layer on top of a solid traditional doc structure.

By meeting these non-functional requirements, MemoryLink will not only deliver its features but do so in a way that is **trustworthy, efficient, and easy to work with** for our internal stakeholders.

Architecture & Scaffolding

In this section, we describe the high-level architecture of the MemoryLink MVP and how the project will be structured (scaffolded). The design ensures a **crisp separation of concerns** – particularly between local components and any future cloud components (hybrid boundary) – and makes it easy to containerize and deploy on different environments.

System Architecture Overview

MemoryLink's MVP architecture consists of a few core components working together (all running on a single machine in MVP):

- **MemoryLink API Server:** This is the main application service that exposes HTTP endpoints (REST API) for memory operations (add, search, etc.). We plan to implement this as a lightweight web server (for example, using **FastAPI** or **Flask** in Python, or an equivalent in Node.js if we choose JavaScript/TypeScript). The server handles request parsing, calls into the memory logic, and returns responses. It will be stateless (no session data kept between requests).
- **Vector Store / Embedding Index:** A component responsible for storing vector embeddings of memory content and performing similarity search. For MVP we have two approaches:
- *Embedded Library:* Use an in-process vector search library (e.g., Faiss via `faiss-python`, or **ChromaDB** which manages embeddings and metadata in a local SQLite). This keeps everything in one process for simplicity, but could be limited by memory.
- *External Service:* Run a small vector database as a separate service (container) such as **Qdrant** or **Weaviate** (both have single-node open source versions). The MemoryLink API server would then communicate with this via its client library or HTTP API. This approach is more modular – aligning with the "boring API adapters" concept by using standard interfaces.
- We lean towards using an **embedded vector store (Chroma)** for simplest integration in MVP, but will encapsulate it so we can swap it out. The vector store is what provides the core "memory similarity search" capability [9] .
- **Metadata & Persistence Store:** Alongside the vector index, we need to persist the memory entries with their metadata and possibly the raw text (encrypted). Options:
- Use a **lightweight database** (like SQLite or PostgreSQL). Given ease of use, we might start with SQLite (file-based, no extra service) for the metadata. If using ChromaDB, it might handle metadata itself; if using Qdrant, we might use Qdrant's collections for metadata or a separate small Postgres.
- The metadata store holds tables for Memory entries (with fields: ID, user, content_encrypted, timestamp, tags, embeddingVector, etc.). If using SQLite, we can also store the embedding vectors as blobs, but that's less efficient to search – that's why a vector index is preferred. So likely, metadata DB holds everything *except* the vector index which is managed by the vector store.
- **Encryption Layer:** This is not a separate service but a module in the API server that encrypts/decrypts content as it goes to/from the persistence. For example, when adding a memory, the server

will call an `encrypt(text)` function (using the configured key) before saving to DB. When retrieving, it will decrypt before returning results.
- **Client Interfaces:** Even though not separate services, it's worth noting how clients interact:
- **REST API** – primary interface for agents and tools (as discussed).
- **CLI/Makefile** – developer convenience interface. This isn't part of the runtime architecture per se, but our distribution includes a CLI script that internally calls the REST endpoints (e.g., using `curl` or Python requests). It provides a human-friendly way to do operations during testing or onboarding.
- In the future, an SDK (e.g., a Python library or Node package) could wrap the REST calls for even easier integration, but for MVP the raw HTTP calls suffice.
- **Future Cloud Sync (not in MVP):** To illustrate the "hybrid boundary," if we later add a cloud component, it would likely be a **synchronization service or cloud-hosted memory hub** that the local MemoryLink could push to or pull from. In our architecture, this would be an *optional connector* module that takes events from the local store (perhaps via a change feed or user command) and sends encrypted data to a cloud store. The cloud part would never receive plaintext, and the local user would hold keys – thus the boundary is "crisp" and privacy-preserving. For MVP, we simply note where this would attach (likely on the API server side as an extension or separate sync agent watching the DB).

Architecture Diagram: *(Descriptive)* The MemoryLink system can be visualized as follows: - The **MemoryLink API Server** sits in the middle. Incoming HTTP requests (from AI agents, IDE plugins, or CLI) hit this server. - On an `Add Memory` request, the API server: 1. Takes the text and metadata from the request. 2. Passes the text to an **Embedding Generator** (a sub-module or external API) to get a vector representation. 3. Encrypts the text (if encryption enabled) and stores the encrypted text + metadata (and possibly the vector) in the **Persistence Store** (DB). 4. Stores the vector in the **Vector Index** (if using separate vector DB). 5. Returns a success response. - On a `Search Memory` request, the API server: 1. Takes the query (text and/or filters). 2. Passes the query through an **Embedding Generator** (for semantic search) to get a query vector (or uses keyword if it's a pure keyword search). 3. Queries the **Vector Index** for similar vectors (or does a metadata filter query in the DB if keyword-based). 4. Gets a list of candidate memory IDs from the vector store (with similarity scores). 5. Fetches those entries from the **Persistence Store** (DB) by IDs. 6. Decrypts the content of those entries and returns the results to the client in a response. - **Supporting Services:** If using external components like Qdrant or Postgres, these run as separate containers accessed by the API server. In a Docker Compose setup, for instance, we'd have `memorylink-api` container, `vector-db` container, and maybe `metadata-db` container, all on a private network. The API uses environment variables to know the host/port of these. - **Boundary Clarity:** All the above components run on the user's machine. There is no implicit communication to any cloud service. Any future addition (like syncing to a cloud) would be a clearly separate process or thread that the user opts into. This ensures we maintain a clear distinction between "local operations" and "external operations" – fulfilling the crisp hybrid boundary goal.

Technology Stack & Tools

For the MVP implementation, we choose technologies that allow rapid development within 30 days, align with our team's expertise (internal developers), and meet the requirements:

- **Programming Language: Python** is a strong candidate for the API server, given its rich ecosystem for AI and data (embedding models, etc.), and fast development speed. Additionally, many internal tools and AI agents might already be using Python, so having a Python-based memory server means we could even embed it or interface easily if needed. Alternatively, **Node.js** could be used if we want JS integration, but we'll go with Python + FastAPI for this plan due to familiarity and libraries.

- **Web Framework: FastAPI** (with Uvicorn ASGI server) will allow us to define REST endpoints quickly and comes with automatic documentation (Swagger UI generation), which is a bonus for internal devs to test the API. It's async-ready and high-performance. If Python, we'll use FastAPI; if we pivot to Node, we'd use Express or NestJS.
- **Vector Database / Index: ChromaDB** is an easy option (pip installable, can use local disk storage for persistence, and supports adding metadata with each embedding). Using Chroma means we don't need an external DB for vectors; it internally uses SQLite to persist. Another option is **Faiss** for pure in-memory vector search (with periodic saves to file), but that would require more custom code to manage metadata. We lean towards Chroma for MVP simplicity.
- If ChromaDB, the architecture simplifies slightly: the MemoryLink API server can use the Chroma Python library to add/query the "memory" collection. Chroma will handle storing vectors + metadata on disk (with encryption possible at application layer).
- If we choose an external service like Qdrant, we would run Qdrant's Docker image and use its REST API or client lib. This adds overhead in deployment (two services instead of one), so likely keep it simple with an embedded store for now.
- **Database for Metadata:** If using Chroma, not needed separately. If we needed more structured queries or to store larger content, we might use **SQLite** for storing full encrypted text and link entries by ID to vector store entries. SQLite requires no setup and can be accessed via SQLAlchemy in Python. This can be encrypted at the filesystem level or via an extension for encrypted SQLite. For MVP, regular SQLite with the content encrypted at application layer is sufficient.
- **Embedding Generation:** To do semantic search, we need embeddings:
- **Local Model:** Use a small embedding model (for example, SentenceTransformers like `all-MiniLM-L6-v2`) which can run on CPU reasonably fast. We can bundle this model or have the user download it. This avoids external API calls and keeps things local. The downside is slightly slower and bigger footprint.
- **External API (optional):** As a fallback or for better quality, allow using OpenAI's embedding API or similar by configuring an API key. This would break the "strictly local" rule, but it could be optional if user chooses better quality over privacy for certain cases. By default, we'll use local to stick to local-first philosophy.
- We will abstract the embedding generation behind an interface (so it can be swapped easily). Maybe provide both options in config.
- **Encryption Library:** Use a well-known library like **PyCryptodome** or **cryptography** in Python to perform AES-256 encryption of text. We'll generate a key from a passphrase using a KDF (Key Derivation Function) and store that (or require it each run). Simpler: use a static key in .env for now (since internal usage, we can manage keys in environment variables or a config file).
- **Docker & DevOps:** Use **Docker** to containerize the API server. The Dockerfile will likely be based on Python 3.11-slim image, install the required packages (fastapi, chromadb, etc.), copy the app code. We will also create a Docker Compose YAML that can bring up:
- The API container (exposing port e.g. 8080).
- Possibly a separate container for vector DB if using external (not if using Chroma in-process).
- Possibly a container for a UI (if we had a tiny front-end) but likely not in MVP.
- The advantage is one command brings the system up.
- **Project Structure (Scaffolding):** We will organize the code repository as follows:
- `app/` (or `memorylink/` as package) – containing the FastAPI app code:
    - `main.py` (entry point, initializes FastAPI, sets up routes).

    - `routes/` – API endpoint route handlers (e.g., memory.py containing add_memory and search_memory functions).
    - `services/` – core logic separated from HTTP (e.g., `memory_service.py` with functions to add/search that interact with DB and vectors).
    - `db/` – database related code (initializing Chroma or DB connection, encryption utilities).
    - `models/` – (if needed) Pydantic models or data classes for requests and responses.
    - `config.py` – configuration reading (for keys, file paths).
    - `embeddings/` – code or scripts to initialize the embedding model or call external API.
    - Maybe `cli/` – a folder for CLI scripts if we include a Python-based CLI (though we might just use Makefile with curl, so not complex CLI code).
- `Dockerfile` & `docker-compose.yml` at root for container setup.
- `Makefile` at root for convenience commands (setup, run, test, etc.).
- `README.md` for documentation (which will contain the gamified instructions in segments).
- `docs/` folder (if we write more extensive docs or to-be-published documentation).
- `tests/` for any test code.
- This structure ensures clarity (web/API vs logic vs data management). It's also familiar to many, improving maintainability.

Docker and Kubernetes Path

As per requirements, **Docker on developer laptops** is the first target deployment, with a path to **Kubernetes** later: - In MVP, we focus on Docker Compose for local deployment. We will test on at least Linux and macOS (and Windows via Docker Desktop) to ensure the experience is smooth. The documentation will have a section "Running MemoryLink" which basically says *"Ensure Docker is installed. Then run* `docker-compose up -d` *to start the service. Use* `docker-compose logs -f` *to see logs."* We'll also integrate this with the Makefile (so `make start` runs the compose). - For Kubernetes readiness, our container images and application will be built stateless and configurable: - We won't hard-code any hostnames or assumptions; instead use env vars (which can be provided via ConfigMap/Secret in K8s). - No local filesystem dependence except the mounted volume for data. In K8s, that can be a PVC (PersistentVolumeClaim). We document that all state resides under, say, `/data` volume which can be mounted. - We will avoid using Docker-in-Docker or any incompatible stuff – just a straightforward container. - After MVP, writing a Helm chart or K8s yaml would be trivial since it's one deployment with perhaps a service and one volume. - We also consider that internal teams might later deploy this on an internal server or cloud – so we ensure TLS can be added (FastAPI can sit behind a reverse proxy with SSL, or we can allow configuring Uvicorn to use SSL certs). For MVP, this is not done by default (since local usage, `http://localhost` is fine), but it's noted in docs how to secure it if deploying to a server.

Overall, the architecture is aimed at fulfilling the core needs (shared memory with local-first design) while being simple enough to implement in 30 days. By using existing components (FastAPI, Chroma, etc.) and containerization, we reduce custom code and ensure stability.

Implementation Plan (30 Days)

To successfully build this MVP in 30 days, we will follow a phased implementation plan with clear milestones each week. The plan allocates time for development, testing, and documentation (including the gamification aspects). Here's the breakdown:

- **Week 1: Foundation and Setup**
- *Task 1.1: Project Setup:* Initialize the code repository with the scaffolding structure described (folders, placeholder files, basic FastAPI app that runs "Hello World"). Set up the development environment and ensure Docker is configured. **Deliverable:** A running Docker container that serves a dummy endpoint (proof that our pipeline works).
- *Task 1.2: Core Data Schema:* Define the data models for memory entries. For MVP, this might be a Pydantic model `MemoryEntry` with fields id, text, tags, timestamp, user. Decide on using ChromaDB or SQLite+Faiss; implement a small prototype of adding an entry to whichever store. **Deliverable:** In-memory add and search functions working in a basic way (without encryption yet). Possibly use a simple list or dictionary for now to simulate.
- *Task 1.3: Embedding Integration:* Choose and test the embedding generation approach. Download a small embedding model (if using SentenceTransformers) and run a sample to ensure we can get a vector. Alternatively, test calling OpenAI embedding API (if we want that option). **Deliverable:** Code snippet or module that given a text returns a vector (and the vector dimension, etc., defined).
- *Task 1.4: Encryption Module:* Implement a utility for `encrypt(text)->ciphertext` and `decrypt(ciphertext)->text` using a fixed key (for now). Use a well-tested method (AES-GCM for example). **Deliverable:** Functions working with a test to encrypt and decrypt a sample string correctly.

- **Week 2: Core Feature Implementation**

- *Task 2.1: Add Memory Endpoint:* Implement the `POST /add_memory` endpoint in the API server. On receiving a request, perform the flow: validate input, generate embedding, encrypt text, store in DB/index. Use a placeholder or simple logic for vector storage (maybe an in-memory list of (id, vector) for this early test). **Deliverable:** Able to cURL an add request and see entry stored (logged or retrievable).
- *Task 2.2: Search Memory Endpoint:* Implement the `GET /search_memory` endpoint. Handle both semantic search (if a query text is provided) and basic filtering. For now, if we haven't integrated the actual vector DB, use a naive similarity (or skip actual similarity until vector store is in). Focus on returning dummy data to shape the response format. **Deliverable:** cURL a search request and get a well-formed JSON response (even if it's empty or dummy data for now).
- *Task 2.3: Integrate Vector Store:* Now replace the placeholder from above with actual integration:
  - If using ChromaDB: instantiate a local persistent Chroma collection at startup. Implement add: store metadata in SQLite (if separate) and add vector to Chroma with metadata. Implement search: query Chroma by similarity and return IDs, then get metadata from DB (or from Chroma if it stores it).
  - If using Faiss: maintain an in-memory index and a separate list mapping IDs to encrypted texts & metadata.

    - **Deliverable:** Real data flow working – adding a memory actually persists (to disk via Chroma or DB), and searching returns actual relevant results. Test by adding a few known entries and searching for them.

- *Task 2.4: Basic Testing and Fixes:* Write a few unit tests for the service layer (e.g., test that adding and then searching returns the expected entry). Also test edge cases like searching with no data, adding an entry with empty text, etc. Fix any bugs uncovered (e.g., encoding issues with encryption, etc.).

- **Week 3: Refinement and Non-Functional Features**

- *Task 3.1: Implement Encryption in Data Path:* If not already done fully, ensure that when data is stored it's encrypted. This might involve deciding how to handle search (we can't encrypt embeddings obviously, since they need to be searchable; but the raw text and any sensitive metadata should be encrypted). Test that the stored data on disk (e.g., in Chroma's SQLite or our DB) is indeed encrypted gibberish and that our search still works (because search uses embeddings, not raw text).
- *Task 3.2: Performance Tuning:* With core features in place, measure basic performance. If using Chroma, check how it performs with say 1000 entries (we can generate dummy entries). Ensure that search is reasonably fast. If any slowness, consider smaller embedding or adjust indices. Also ensure parallel requests don't break anything (maybe simulate two concurrent calls).
- *Task 3.3: Dockerization:* Write the Dockerfile for the API server. Likely a multi-stage build (build dependencies then run). Test building the image. Create docker-compose.yml that includes the API service and any others (if needed, e.g., if using separate DB container). Test that `docker-compose up` successfully brings everything and the API is reachable on localhost. **Deliverable:** Docker images built and the service running fully inside Docker.
- *Task 3.4: Documentation Drafting:* Begin writing the documentation for usage. This includes describing how to run the system (with Docker or alternative), the API endpoints (we can output FastAPI docs for that), and importantly the **gamified tutorial** content. Outline the "story" or sequence of steps we want users to take. Decide on theming (maybe a fun theme like a quest to recover lost memories, etc., to align with the memory concept). **Deliverable:** A rough draft of README or docs that covers installation and basic usage in an engaging way.

- *Task 3.5: Gamification Implementation:** Using the draft above, implement the actual hooks:

    - Write Makefile targets corresponding to the steps we want to gamify (start, add example, search example, etc.). Ensure these targets perform the action (could call curl or use small Python snippets).
    - For each target, craft the console output to be fun. Possibly use color text or ASCII art (not too much time on art, but a little flair like a MemoryLink banner on start).
    - Example: a target `make tutorial` that sequentially runs through steps or guides the user interactively. If ambitious, maybe a Python script can ask user to input a query and then validate if the system returns the expected result (simulating a puzzle).
    - **Deliverable:** By end of week 3, we should be able to have a colleague follow the README and complete the "onboarding quest", providing feedback on the fun factor and clarity.

- **Week 4: Testing, Feedback, and Polish**

- *Task 4.1: Internal Testing (Alpha test):* Have a small group from the internal team set up the system using only the documentation (on their own laptops). Observe or collect feedback: did Docker

Compose work, were there any environment issues, did the gamified instructions make sense and were they enjoyable? Note any confusion or bugs that came up.

- *Task 4.2: Bug Fixes & Improvements:* Based on testing feedback, fix any issues found. Common potential issues: firewall blocking the container, performance hiccups, unclear error messages, missing dependencies, etc. Also refine any gamification text that was confusing or too verbose.
- *Task 4.3: Complete Documentation:* Finalize the documentation, including:
    - A normal quickstart section (for those who just want straightforward steps).
    - The gamified tutorial section (clearly marked as a fun walkthrough).
    - API reference (could just link to the auto-generated docs or include example requests and responses).
    - Architecture notes for future developers (so they understand the system design and how to extend it).
    - Troubleshooting tips for common issues (if any came up during testing).
- *Task 4.4: Performance and Load Testing (Mini scale):* If time permits, simulate a slightly larger usage: e.g., load 5k memory entries and run concurrent queries to see if memory usage and speed hold up. While MVP doesn't need to scale massively, we want to ensure no obvious memory leaks or O(N^2) behaviors. Optimize configuration if needed (maybe adjust vector search top_k, or DB indexing on tags).
- *Task 4.5: Prepare for Handoff:* Since this is for internal teams, ensure that everything needed to continue development is in place:
    - The repository in our internal version control.
    - A short presentation or demo recording of how MemoryLink works.
    - Backlog items for post-MVP (like features we cut or future enhancements, e.g. "implement multi-user support", "build VSCode extension to use MemoryLink", "Kubernetes deployment files", etc.).
    - This ensures that after the 30-day MVP, the project can smoothly transition to the next phase with all knowledge captured.

By the end of Week 4, we expect to have a **functionally complete, tested, and documented MVP** of MemoryLink. Internal teams should be able to run it on their laptops, use the API to store and retrieve information, and experience the novel gamified documentation while doing so.

The implementation plan is aggressive but feasible, leveraging a lot of existing technology to save time. Each milestone is designed to produce a tangible output, ensuring we can course-correct if something runs late. The inclusion of internal testing in Week 4 is crucial to validate that our assumptions (especially around the documentation and fun onboarding) actually work for users.

Gamification in Documentation & Developer Experience

One of the standout aspects of this project is the **gamification of the setup and usage experience**. This section details how we will incorporate game-like elements into the documentation and tooling (Makefile/CLI) to engage internal developers:

- **Thematic Onboarding Story:** We will frame the setup process as a story where the developer is the "hero" unlocking the powers of MemoryLink. For example, the introduction of the README might say: *"Welcome to MemoryLink. You are about to embark on a quest to reclaim lost knowledge across your* *tools. Follow the steps to set up your personal Memory Vault and become the Memory Master of your team!"* This narrative approach sets a fun tone from the start.

- **Levels and Achievements:** The tutorial will be broken into **levels** or steps, each with a clear goal:

- **Level 1 – Summon the Server:** In this level, the user learns to launch the MemoryLink service. Instructions: *"Run* `make start` *to summon your MemoryLink server in a Docker container."* After running it, the console might output something like:

```
Starting MemoryLink...
  Docker containers are up and running at http://localhost:8080
  Congrats! MemoryLink is alive.
(Level 1 complete – You have summoned your MemoryLink server!)
```

  And then prompt: *"Proceed to Level 2: Add a memory."*
- **Level 2 – First Memory Entry:** The user is instructed to add a sample memory. This can be done via a provided script or curl command. For ease, we have a Makefile target: `make add_sample_memory`. This target might call a curl with a predefined JSON (like a memory entry about an example meeting). On success, the output could be:

```
Added sample memory: "Project kickoff meeting notes..."
Memory ID: 12345
  Memory saved in your vault!
(Level 2 complete – First memory added)
```

  And a hint: *"Now, let's try retrieving it – on to Level 3!"*
- **Level 3 – Search the Vault:** Now the user learns to query. The docs might say: *"Try searching for a keyword from the sample memory, e.g.,* `make search QUERY=kickoff`*."* We allow passing a `QUERY` variable to our Makefile or have a default. Running it performs a search and prints results:

```
Searching memories for "kickoff"...
1 result found:
  - [Project kickoff meeting notes] (2025-08-01)
  You recovered a memory from your vault!
(Level 3 complete – Search success)
```

  Possibly display the content or part of it decrypted as proof.

- **Level 4 – Integration Demo (Bonus):** For those who complete basics, we might have an optional level to simulate an integration. For instance: *"Level 4: Use the API from a Python script."* Provide a small Python snippet in docs or a file that calls the API. The user runs it (maybe `make run_integration_demo`) and it shows how an external agent would interface. On running, it might output:

```
Demo script: Asked MemoryLink for 'recent notes'...
AI Assistant received context: "Project kickoff meeting notes..."
  External tool successfully retrieved memory via API.
(Level 4 complete – Integrated an external tool)
```

This reinforces how easy it is to plug in tools.

- **Rewarding Feedback:** Each step gives positive feedback (the checkmarks, “Congrats”, etc.) to reward the user. We use simple symbols like , , or to make it festive. This kind of feedback loop is common in gamification – it makes users feel progress.

- **Easter Eggs and Fun Elements:** Sprinkle a few easter eggs for the curious:
- Maybe a hidden message if they run `make credits` to list project contributors, or `make dance` that prints an ASCII art just for fun.
- A reference to “MemoryLink” name – perhaps an ASCII logo displayed on server start:

```
 __  __ ___
__     __     _        _
   |  \/  |_ _/ / /\ \ \__| | __ _| |_ ___
   | |\/| || |\\ \/  \/ / _` |/ _` | __/ _ \
   | |  | || | >  <  | | (_| | (_| | ||  __/
   |_|  |_|___/_/\_\ |_|\__,_|\__,_|\__\___|
```

(The above or similar could show as a welcome banner).

- Ensure these don’t clutter normal use – possibly only in the interactive tutorial mode.

- **Makefile Implementation Details:** We will use the Makefile not just for building, but for driving this interactive experience:

- Use phony targets for each level. These targets can call shell commands like `docker-compose` or `curl` and then use `echo` to output messages. We can control output formatting (like printing blank lines or using `printf` for coloring if the terminal supports).
- Some logic might be needed (for example, capturing the output of a curl request to determine success). We might write small helper scripts in Python/Bash that the Makefile calls to handle parsing, so the output can be more dynamic.
- Example: `make search QUERY=xyz` target could invoke a Python one-liner that calls the /search endpoint and pretty-prints the results.

- This approach keeps the user from needing to manually craft HTTP requests while learning – the Makefile encapsulates it, but also shows them behind the scenes what’s happening (we can print the actual curl command as an info).

- **Documentation Style:** The written documentation will mirror a game guide:

- Clearly mark sections as “Level 1, Level 2…” with titles like a quest name (e.g., “Level 1: Summon the Server ”).
- Use second-person encouraging tone: “Now you have X, try Y…”, “Great job on completing that step!”.

  - Keep paragraphs short and use bullet lists for instructions to make it skimmable (which is also good practice, not just gamification).
  - Possibly include a storyline element, like: *"You have now gained the ability to recall knowledge at will – a power that will help you in your coding quests ahead."* This adds a bit of narrative fun connecting the tool to their real work.

- **Opt-Out and Professionalism:** Since this is an internal tool, most developers will likely appreciate the creative approach, but we should be careful to not overdo it for those who just want quick info:

  - Ensure that at the end of the README, or in a separate section, we list straight "Commands Reference" or "Manual Setup" for power users. This way, if someone finds the gamified flow not to their taste, they can skip straight to `docker-compose up` and the API references.
  - The gamification should never reduce clarity. For example, when outputting an achievement, we should also clearly state what practical result was achieved (as shown in examples, we both celebrate and inform, e.g., "MemoryLink is running at port 8080" alongside the fun text).

- **Influence on Usage:** By gamifying setup and usage, we hope to **encourage exploration**. A developer who might not otherwise try an integration might do it because it's presented as a fun challenge. This leads to better understanding of the tool's capabilities. It also makes the experience shareable – we can imagine internal team members sharing their "achievement unlocked" moments on chat, which propagates interest. This is especially useful since MemoryLink's value increases with adoption across tools – a bit of friendly competition or curiosity can drive more teams to try it out.

In summary, the gamification element is implemented via the CLI (Makefile and script outputs) and in the tone of documentation. It's an innovative touch to an internal developer tool that we expect will result in higher engagement, faster onboarding, and even enjoyment. We treat the developer experience not just as documentation, but as the first user story of the product itself.

Conclusion

In this plan, we have detailed a comprehensive approach to building the **MemoryLink** MVP in 30 days. By focusing on a clear scope and leveraging a local-first architecture, we ensure that the **hybrid boundary remains crisp** – all personal memory data stays local and secure, and any future cloud interactions will be strictly optional and encrypted. We enumerated the functional requirements that deliver the core value: a unified memory layer that any tool can integrate with via a stable, standard API. Non-functional requirements like security, performance, and scalability considerations guide us in making the MVP robust and future-proof for internal use.

The architecture leverages proven technologies (FastAPI, embedding libraries, vector stores) assembled in a containerized environment (Docker/Docker-Compose) that can later transition to Kubernetes with minimal friction. We have also laid out an iterative implementation plan, ensuring that within each week we achieve milestones – from basic setup in week 1 to a polished, tested product by week 4.

One of the most novel aspects is the **gamified developer experience**: by turning setup and learning into a game-like journey, we aim to maximize internal adoption and make the process enjoyable. This is not just fluff – it's a strategic choice to tackle the common challenge of developer tool fatigue. An engaging onboarding means more team members will give MemoryLink a try and quickly grasp its benefits, accelerating feedback and iterative improvement.

By the end of the 30-day MVP, we expect to have: - A working MemoryLink service that internal agents and IDE extensions can call to **store and retrieve memory**, fulfilling the vision of seamless context continuity [10] [11] across tools. - Demonstrated **local-first operation** with data privacy intact [8], aligning with our values of user control and security. - Documentation and tooling that not only instruct but also **delight** our internal users, setting a positive tone for further development.

MemoryLink's MVP will provide a strong foundation to build upon. With the core in place, we can later expand into collaborative features, cloud sync, richer analytics, and integrations – always keeping the core principles of simplicity, security, and interoperability at the forefront.

Sources: - Bijit Ghosh, *"Building a Memory Application Server for Cross-Application AI"* – Introduction of a persistent memory layer concept [2] [5] and design principles like local-first and encryption for privacy [4]. - Pieces.app Blog – *"Your AI connector for Warp"* – Example of a local-first, secure memory approach in developer tools [8] which validates the importance of offline support and deep integration without cloud dependence.

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