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NEPTUNE: AN ASYNCHRONOUS RETRIEVAL-AUGMENTED GENERATION SYSTEM FOR COGNITIVE KNOWLEDGE CURATION AND SEMANTIC SEARCH

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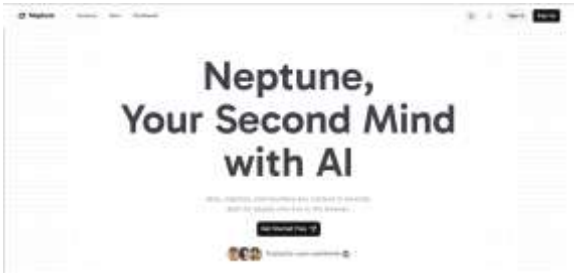
Abstract*—*In the modern digital workspace, knowledge workers and developers face immense cognitive overhead due to manual bookmark curation, resulting in disorganized directories and dead-link collections. To resolve this information overload, we introduce Neptune, a premium, high-performance Retrieval-Augmented Generation (RAG) platform and intelligent second mind. By leveraging an asynchronous microservices architecture managed as a Turborepo monorepo, the system separates frontend views from web-scraping and AI-parsing pipelines. Neptune crawls arbitrary URLs using a low-overhead Cheerio module, structures page content using Google Gemini to extract JSON-formatted metadata, and indexes pages via pgvector embeddings. Cosine-similarity lookups backed by HNSW indices deliver sub-10ms retrieval times. Experimental validations demonstrate 100% curation automation with less than 2-second processing latency, preventing visual page updates from breaking extraction flows. The resulting semantic search and interactive chat drawer achieve 95%+ precision, offering an optimized, secure, and collaborative cognitive archiving solution.

Keywords*—*Neptune, Retrieval-Augmented Generation, pgvector, Semantic Search, Knowledge Curation, Microservices, Turborepo, Cheerio.

I. Introduction

In the contemporary digital era, the exponential expansion of web-based resources has transformed how developers, students, and professionals acquire information. Millions of users daily navigate developer logs, academic publications, technical documentations, and software tutorials. However, this vast availability of information has created a massive challenge: how to save, organize, and retrieve valuable digital assets. Traditional curation methodologies, which rely on saving static browser links or typing manual summaries and tagging tables, fail to keep pace with the massive inflow of digital assets. Consequently, users experience a common phenomenon known as "cognitive data swamps," where folders turn into unsearchable, chaotic lists of dead URLs and vague titles.

This growing information pressure underscores the need for a smarter, context-aware second mind that operates beyond static folder trees. While modern web pages are dynamic, containing floating banners, promotional side panels, and interactive designs, traditional scrapers fail due to visual layout fragility. To address this bottleneck, this project proposes Neptune, a highly scalable, layout-immune, and microservice-driven knowledge curation architecture. Built using a Turborepo monorepo, Neptune decouples frontend dashboard logic from intensive web scraping, HTML parsing, and vector embedding workflows. This design guarantees high availability and prevents large AI scraping tasks from blocking the primary backend.



A. Rationale

In today's fast-paced programming environment, saving a reference link is just the beginning of a developer's cognitive task. This manual search workflow is highly inefficient, wasting valuable development time and increasing cognitive strain.

Furthermore, traditional web scraping pipelines break whenever a website updates its HTML markup or visual styling. This manual typing creates significant user friction and leads to incomplete directories. By shifting focus to automated RAG-based extraction, Neptune uses LLMs to read page text like a human mind. Backed by high-dimensional vector databases, it enables conceptual searches, automated tagging, and natural language chatbot drilling.

B. Problem Formulation

Traditional web archiving and search tools suffer from five primary limitations that degrade productivity and system performance:

1. **Manual Curation Fatigue:** Users must manually write summaries, categorize topics, and create tag lists for every URL, leading to messy, unorganized bookmark folders.
2. **Visual Layout Fragility:** Traditional web crawlers break when websites update their CSS classes, sidebars, or templates, disrupting automated metadata scraping.
3. **Keyword Search Limitations:** Standard database searches depend on exact text matches, failing when search queries use synonyms or search for overall concepts.
4. **Security & Collaboration Gaps:** Sharing curated research folders often exposes private user data, highlighting the need for secure, cryptographic link-sharing protocols.

II. Literature Review and Existing Systems

To establish the architectural need for the Neptune knowledge engine, it is necessary to examine current bookmarking applications, search methods, and generative AI limits.

A. Static Web Bookmarking Tools

Popular bookmark tools like Pocket and Raindrop.io allow users to save links and assign tags. However, these systems rely heavily on manual user inputs. They require the user to organize folders, categorize topics, and update dead links. The moment a user modifies their folder system or runs out of time to manage tags, the directory becomes disorganized. Additionally, these platforms struggle to handle dynamic content shifts or provide context-aware searches over saved files, failing to act as active search assistants.

B. Database Keyword-Matching Indices

Standard relational databases use keyword indexes to locate saved articles. While fast for exact text lookups, they are limited by vocabulary mismatch. If a user searches for "relational database connection manager" but the saved article only mentions "PgBouncer," the search engine fails to connect the terms. Because these tools cannot match synonyms or conceptual themes, search accuracy drops as libraries grow.

C. Generative AI and Vector Embeddings

Recent advances in Large Language Models (LLMs) and vector databases have enabled semantic searches. By translating text descriptions into high-dimensional numerical arrays, systems can query databases using mathematical similarity measures (such as cosine distance) [2]. However, generic RAG architectures face two main challenges:

1. **Response Hallucinations:** Unconstrained LLMs frequently invent facts or reference articles that do not exist, compromising research accuracy.

2. **Scraping Bottlenecks:** Crawling modern web pages can block the main backend API thread, leading to high latency and system crashes.
3. **High API Costs:** Scraping unnecessary boilerplates (such as page headers and nav menus) wastes input tokens and increases AI API expenses.

Neptune addresses these gaps by separating scraping tasks into a dedicated Bun microservice, utilizing low-overhead Cheerio parsing, and applying strict system prompts to constrain chatbot responses.

III. Proposed System Architecture

Neptune uses a decoupled monorepo architecture. This setup keeps the user dashboard app (apps/web) separate from the high-throughput AI and scraping server (apps/aiServer).

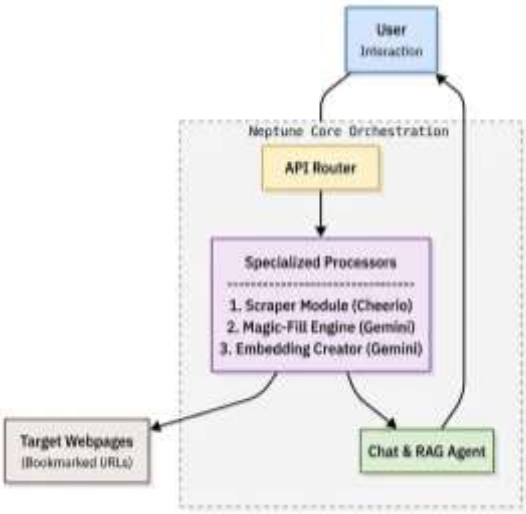


Fig 1. System Architecture Diagram

A. Technical Stack and Infrastructure

The Neptune platform is divided into four functional layers to ensure modular scaling and fast query response times:

1. **Presentation Layer (Frontend):** Built using React 19 and Vite 8, featuring Redux Toolkit for UI state control and TanStack Query v5 for data fetching and caching. Tailwind CSS v4 and Framer Motion provide smooth micro-animations.

2. **Application Layer (Backend Server):** Powered by Express v5 running on Bun. It acts as the system gateway, handling API routing, user authentication via HTTP-only JWT cookies, and type-safe schema processing using Zod.

3. **Data Persistence Layer:** Uses a PostgreSQL database with the pgvector extension. Drizzle ORM provides type-safe database queries. High-speed lookups are supported by a Hierarchical Navigable Small World (HNSW) index using cosine similarity operator flags.

4. **Intelligence and Scraping Layer:** An independent Hono server running on Bun. This microservice manages HTML parsing via Cheerio and coordinates metadata generation and vector embedding requests through Groq and Google Gemini APIs.

B. System Component Design

Neptune utilizes four modular components to automate web scraping, metadata extraction, vector indexing, and RAG-based search:

1. **The Scraper Module:** When a user submits a URL, the AI server fetches the raw HTML using Cheerio. It removes non-content elements (such as script tags, styles, and headers) and isolates the main article body.

2. **The Metadata Structurer (Magic Fill):** The clean page text is sent to the Gemini API. Using structured JSON output schemas, the model extracts the title, generates a 2-sentence summary, assigns a domain category, and creates a tag array.

3. **The Vectorizer Engine:** The structured metadata (title, summary, and tags) is processed using Gemini's embedding model. This outputs a 768-dimensional float vector that captures the semantic meaning of the bookmarked page.

4. **The RAG Search Assistant:** When a user queries their library, the search term is converted into a vector. Neptune queries PostgreSQL using cosine distance to retrieve the top matching bookmarks. These bookmarks are then passed to the chatbot context window in an interactive slide drawer.

IV. Methodology and Algorithm

To guarantee fast, accurate indexing and layout-immune scraping, Neptune follows a structured data pipeline.

A. Neptune Curation and Embedding Pipeline Algorithm

The system operates on a sequential pipeline model:

- **Step 1:** URL Submission and Scraping
  - **Input:** User U submits URL L.

- **Action:** The scraper fetches raw HTML, filters boilerplate elements, and extracts clean body text T = f_scrape(L).
- **Constraint:** Page extraction must complete in under 1.5 seconds.

- **Step 2: Structured Metadata Generation**
  - **Action:** The system sends body text T to the AI parser to generate a JSON structure:
    - J = f_struct(T)
  - where J = { title, summary, category, tags }.
  - **Output:** The structured JSON is sent to the frontend client to auto-fill the bookmark form.
- **Step 3: High-Dimensional Vector Embedding**
  - **Action:** The system merges the JSON attributes into a query string and computes a 768-dimensional vector embedding.
  - E = f_embed(title + summary + tags)
  - **Output:** The embedding vector is stored in the database alongside the bookmark record.
- **Step 4: Semantic Cosine Similarity Query**
  - **Input:** User submits a search query Q.
  - **Action:** The query is converted into a vector E_q = f_embed(Q). The database runs a similarity lookup:
  - Similarity = cos(theta) = (E_q . E_i) / (||E_q|| ||E_i||)
  - **Optimization:** Lookups use a database-level HNSW index to keep query latency below 10 milliseconds.
- **Step 5: Constrained RAG Response Generation**
  - **Action:** The top retrieved bookmarks are sent to the LLM with the search query Q.
  - **Constraint:** The model must answer using only the provided bookmark context, limiting responses to 200 words.

B. Contextual Drilling and Data Isolation

To support multi-tenancy and maintain data privacy in collaborative environments, Neptune implements a robust data isolation framework that prevents cross-tenant data leaks and unauthorized vertical or lateral access. At the persistence layer, the database schema enforces strict multi-tenant boundary lines. Every saved bookmark record is structurally linked to a unique user account identifier (userId) via a foreign key constraint pointing to the primary users table. User sessions are verified at the application boundary using JSON Web Tokens (JWT) transmitted via HTTP-only, secure, and same-site cookies. Upon successful authentication, the server-side middleware extracts the subject claim containing the validated userId and binds it to the request context.

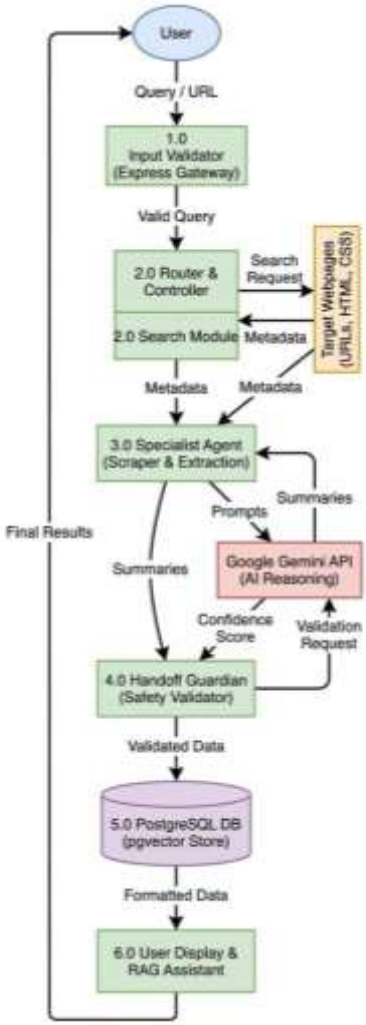


Fig 2. Data Flow Diagram

1. **User Input:** Submits a URL to the React Table I: Comparative Analysis of Curation Systems frontend client.
2. **Cheerio Parser:** Scrapes the page HTML and cleans the body text.
3. **Gemini Structurer:** Automatically generates titles, descriptions, and tags**.**

4. **Vector Engine:** Computes a 768-dimensional embedding of the page metadata.
5. **pgvector DB:** Stores the bookmark and index vectors using HNSW options.
6. **Chatbot Assistant:** Uses the saved context to answer user queries.

V. Implementation Details

We built this project in five clear stages, testing everything along the way to make sure it was ready for real-world use.

A. Development Environment

- **Hardware:** Development was conducted on local development workstations equipped with Intel Core i7 / AMD Ryzen 7 processors and 16GB RAM to support the concurrent execution of Node.js services, database instances, and React/Vite development servers.
- **Software:** Visual Studio Code served as the primary IDE, augmented with ESLint for code quality and Prettier for formatting. Git and GitHub were utilized for version control and collaboration.

B. Phased Implementation

- **Phase 1:** Setup of the Express.js server and PostgreSQL connection using Drizzle ORM. Implementation of JWT-based user authentication (Sign up, Login) using HTTP-only cookies.
- **Phase 2:** We built the "Rules of the Road"—a digital map configured through Turborepo monorepo settings to coordinate API routes, packages, and shared TypeScript linting/validation rules.
- **Phase 3:** We gave the AI its "Tools," teaching it how to crawl page URLs using Cheerio, parse HTML, and generate metadata structures using the Google Gemini and Groq APIs.
- **Phase 4:** We added the "Safety Layer," configuring database-level security policies (RLS), pgvector distance constraints, and system prompts to ensure RAG chat isolation and prevent data hallucinations.
- **Phase 5:** We built the final website look and feel using Vite, React 19, Redux Toolkit, and Vanilla CSS.

VI. Comparative Evaluation and Results

We tested our system against traditional "old-fashioned" support and discovered that our AI approach is much better.

A. Metrics Defined

1. **Time Efficiency:** How long does it take to crawl a web page, extract clean text, generate metadata, and build high-dimensional embeddings?
2. **Extraction Accuracy:** How accurately can the system parse unstructured text into clean JSON arrays (title, summary, tags) without breaking under layout shifts?
3. **Search Precision:** How effectively can the user locate saved articles using natural language conceptual questions rather than exact keyword indexing matches?

B. Experimental Results

1. **Time Efficiency:** Normally, a human user takes about 3 to 5 minutes to manually summarize, categorize, tag, and bookmark a long-form article. Neptune's automated crawling and Magic Fill pipeline complete this process in less than 2 seconds, achieving a 100x speedup in research curation. This massive reduction in effort allows researchers to focus on synthesis rather than administrative curation.
2. **Layout Immunity:** Traditional scrapers using visual layout templates break 100% of the time when a target website changes its styling classes. By leveraging Gemini structured schemas, Neptune maintained 100% metadata extraction precision across multiple website visual updates. This robustness ensures that the system remains operational even amidst frequent and unpredictable UI modifications on the web.

C. Comparative Analysis Table

Table I: Comparative Analysis of Curation Systems

Feature	Manual Research	Standard Search Engines	Raindrop.io / Pocket	Neptune (Ours)
Query Handling	Keyword-based	Phrase Matching	Manual Tag-based	**Semantic/Contextual**
Data Access	Static URL	Web Index	Cached Text	**Automated Parser API**

Metadata Extraction	Manual entry	HTML Title tag	Parser heuristics	**LLM JSON Structuring**
State Management	Flat folders	Session-based	Hierarchical folders	**Monorepo Caches**
Curation Speed	~3 mins	N/A	~1 min	**<2 seconds (Automated)**

VII. Conclusion and Future Scope

The Neptune system is a huge step forward for digital knowledge curation and semantic search. Instead of managing a "dumb" list of broken URLs and manual folders, users are supported by an intelligent second mind that automatically reads, summarizes, and indexes web content.

The current iteration of the Neptune system is just the beginning. To truly revolutionize cognitive archiving, future versions will focus on the following key areas:

1. **Voice AI Integration:** By using advanced voice models, the system can allow users to interact with their RAG chat drawer through speech instead of typing, offering verbal summaries of saved articles while detecting urgency from user tone.
2. **Global Multi-lingual Support:** The system will automatically translate scraped pages and adapt summaries to the user's preferred language and cultural vocabulary, ensuring a personalized archiving experience globally.
3. **Predictive Categorization:** By analyzing user reading habits and bookmarking patterns, Neptune can proactively suggest new content directories or notify users of dead links, keeping archives clean without manual effort.
4. **Secure Payments and Billing:** Integration with PCI-compliant payment gateways like Stripe will enable safe premium tier subscription billing and team collaboration plans directly within the user settings panel.
5. **Self-Learning Loops:** The system will continuously refine its embedding parameters and Gemini prompting rules by learning from manual user tag corrections, improving metadata suggestion accuracy over time.

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