

GeoAgent: An Agent-Based QGIS Plugin for Natural-Language-Driven Geospatial Analysis with Multi-Backend Large Language Model Support

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Abstract

Geospatial analysis is essential across the earth and environmental sciences, yet conventional geographic information systems (GIS) rely on a procedure-oriented paradigm that demands substantial operational expertise. We present **GeoAgent**, an open-source QGIS plugin that enables goal-driven geospatial workflows through natural language conversation powered by large language models (LLMs). GeoAgent features two operating modes: a *General* mode for exploratory querying and layer management, and a *Processing* mode for multi-step workflow execution. Built on LangGraph state machines, the system decomposes requests into dependency-ordered task queues, discovers algorithms across the entire QGIS Processing registry (~250+ native, GDAL, GRASS GIS, and SAGA tools) via lexical scoring on LLM-generated keywords, introspects parameter schemas at runtime, and executes workflows with LLM-steered error diagnosis and retry loops. Schema-validated structured outputs ensure consistent performance across interchangeable cloud (OpenAI, Google Gemini, Anthropic) and local privacy-preserving (Ollama) backends. We demonstrate GeoAgent through a reproducible flood-exposure screening case study using a bundled dataset and compare its architecture against existing LLM-GIS integrations. GeoAgent is released under the MIT license on the official QGIS Plugin Repository.

Keywords: QGIS; Large language models; LLM agents; Natural-language interfaces; Geo-processing; Open-source GIS; Agentic workflows.

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1 Introduction

Geospatial analysis is fundamental to research across the earth and environmental sciences (Chen et al., 2020; Mansourihanis et al., 2023; Ramírez Montalvan et al., 2026), yet traditional geographic information system (GIS) platforms rely on a procedure-oriented paradigm (Zhu et al., 2021) that creates a steep expertise barrier for non-specialist users (Carroll et al., 2014; Marra et al., 2017; Wells et al., 2021; Ramirez Aranda et al., 2023). To accomplish even routine spatial tasks, users must locate appropriate algorithms among hundreds of candidates in the QGIS Processing registry (including native, GDAL, GRASS GIS, and SAGA tools), configure parameter-heavy dialogs, and manually route intermediate data across multi-step workflows. While recent advances in large language model (LLM) tool learning (Wang et al., 2024; Qin et al., 2025; Qu et al., 2025) and state-machine orchestration frameworks like LangGraph (LangChain, Inc., 2024) offer a pathway toward goal-driven GIS interfaces (Zhu et al., 2021; Li and Ning, 2023), existing LLM–GIS integrations (e.g., Zhang et al., 2024; Mansourian and Oucheikh, 2024; Akinboyewa et al., 2025; Ning et al., 2025; Luo et al., 2026) leave three main gaps:

1. **Execution Mechanism:** Most current systems generate free-form code (e.g., PyQGIS scripts) (Mansourian and Oucheikh, 2024; Akinboyewa et al., 2025), which introduces non-determinism and verification challenges (Ouyang et al., 2025), rather than configuring existing, tested algorithms directly from the host GIS registry.
2. **Deployment & Privacy:** Existing tools are predominantly tied to single cloud providers (Zhang et al., 2024; Akinboyewa et al., 2025), lacking local inference options required by institutions operating under strict data-governance or privacy constraints.
3. **In-GIS Workflow Orchestration:** Systems rarely support multi-step task chaining with automated error diagnosis and steered retry loops directly within the desktop GIS environment (IntelliGeo, 2024; QChatGPT, 2024).

To address these limitations, we introduce **GeoAgent**, an open-source QGIS plugin that embeds a lightweight, graph-structured agent architecture directly within QGIS. GeoAgent makes the following key contributions:

- **Dual-Mode Agent Architecture:** Implements a *General* mode for conversational data exploration and attribute querying, and a *Processing* mode for executing multi-step geoprocessing workflows.
- **Registry-Wide Geoprocessing Engine:** Decomposes natural-language requests into dependency-ordered task queues, discovers algorithms across the full QGIS Processing registry (~250+ native, GDAL, GRASS GIS, and SAGA tools) via lexical scoring on LLM-generated keywords, inspects parameter definitions at runtime, and executes workflows with LLM-steered error diagnosis and retry loops.
- **Multi-Backend & Privacy-Aware LLM Support:** Provides a provider-agnostic abstraction supporting OpenAI, Google Gemini, Anthropic, and local Ollama backends, relying on schema-validated structured outputs for cross-model consistency.

- **Open-Source Implementation & Reproducibility:** Released under the MIT license on the official QGIS Plugin Repository, complete with a bundled demonstration dataset and a cross-model benchmark evaluation protocol.

2 Software Architecture and Implementation

2.1 System Overview & Operating Modes

GeoAgent is implemented as an open-source, pure-Python QGIS plugin structured across five functional layers: a Qt-based user interface, a thread-management layer for UI responsiveness, an agent orchestration layer built on LangGraph (LangChain, Inc., 2024), a tool layer wrapping PyQGIS APIs, and the underlying QGIS Processing Framework (Figure 1). Rather than generating free-form code, GeoAgent delegates spatial operations exclusively to curated, tested algorithms within the host GIS registry, encompassing native, GDAL, GRASS GIS, and SAGA tools.

To accommodate primary patterns of GIS usage, GeoAgent operates in two distinct modes, each implemented as its own LangGraph state machine (Figure 2). In *General* mode, the plugin provides a two-node conversational reasoning loop for exploratory tasks such as querying layer schemas, inspecting attributes, filtering features, zooming, and managing projects. In *Processing* mode, the system functions as a state-machine workflow engine that decomposes complex natural-language requests into dependency-ordered task queues and executes multi-step geoprocessing pipelines directly within the open project.

2.2 Multi-Step Workflow Engine and Geoprocessing Pipeline

When operating in Processing mode, natural-language requests pass through a structured multi-stage execution pipeline. First, an LLM decomposes the user prompt into an ordered task queue with explicit task dependencies, search keywords, and explicit parameter values. Each task is then routed either to direct tool execution for conversational actions or to the geoprocessing sub-graph for spatial analysis.

For tasks requiring spatial analysis, candidate algorithms are discovered across the QGIS Processing registry (~250+ algorithms) by lexically scoring LLM-generated keywords against an indexed algorithm catalog. Algorithm selection follows a three tier strategy that evaluates candidate shortlists, allows full-registry fallbacks, and uses deterministic top-candidate selections to prevent execution blockages.

Once an algorithm is selected, parameter definitions are introspected at runtime directly from the Processing registry. The LLM populates these parameters, performs necessary unit conversions, and references intermediate outputs generated by preceding tasks. Geoprocessing execution funnels through a generic wrapper calling `processing.run()`, which automatically registers resulting vector or raster layers in the active QGIS project.

If execution fails, an error-analysis module submits the traceback and parameters to the LLM, enabling up to two steered retries with alternative algorithms or corrected parameters.

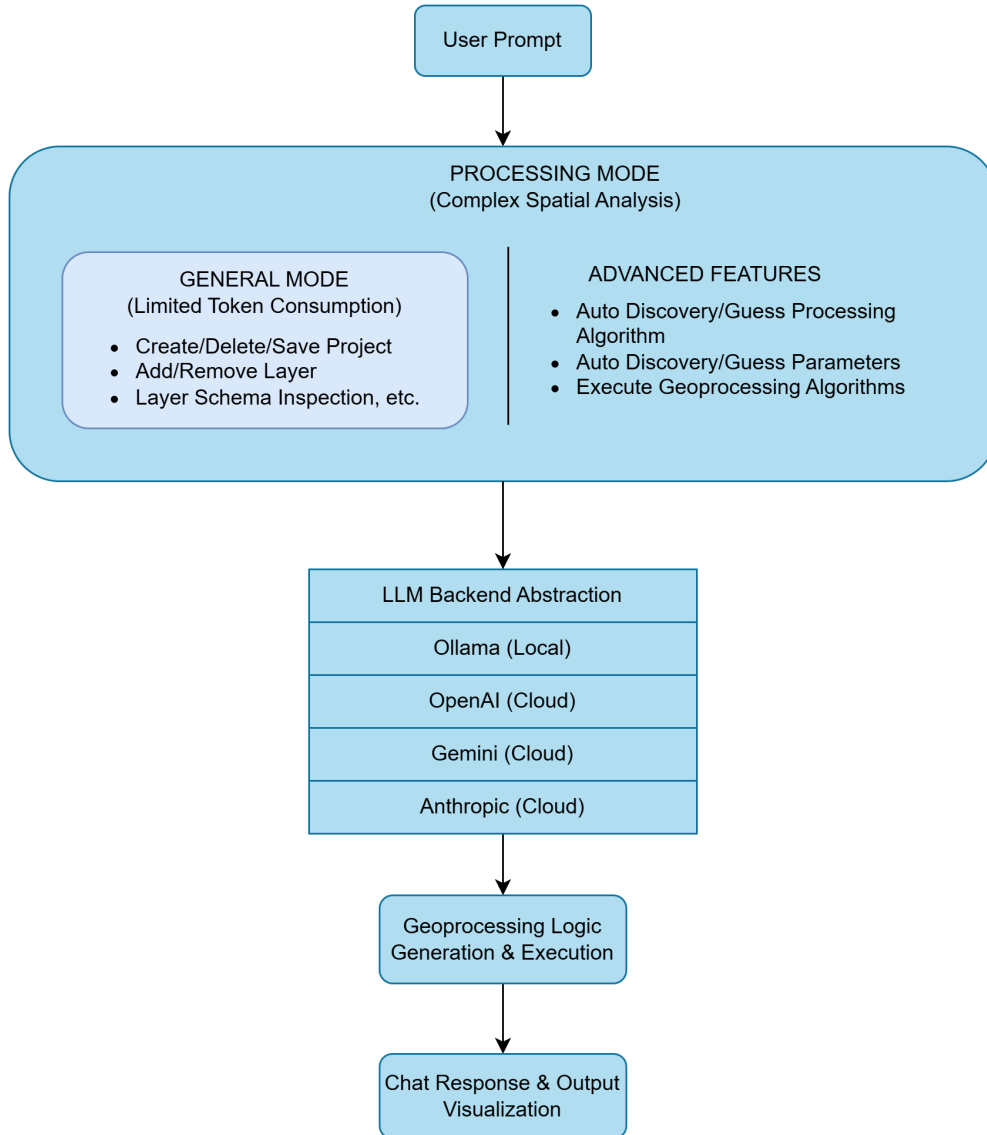


Figure 1: GeoAgent system architecture. Natural-language requests are routed to either a General agent for exploratory operations or a Processing agent for workflow execution. The Processing branch maps requests to QGIS algorithms through a structured tool registry, constructs execution parameters, and returns results to the QGIS project and chat context. A provider abstraction supports interchangeable LLM backends (Ollama, OpenAI, Gemini, Anthropic), enabling both local and cloud deployment.

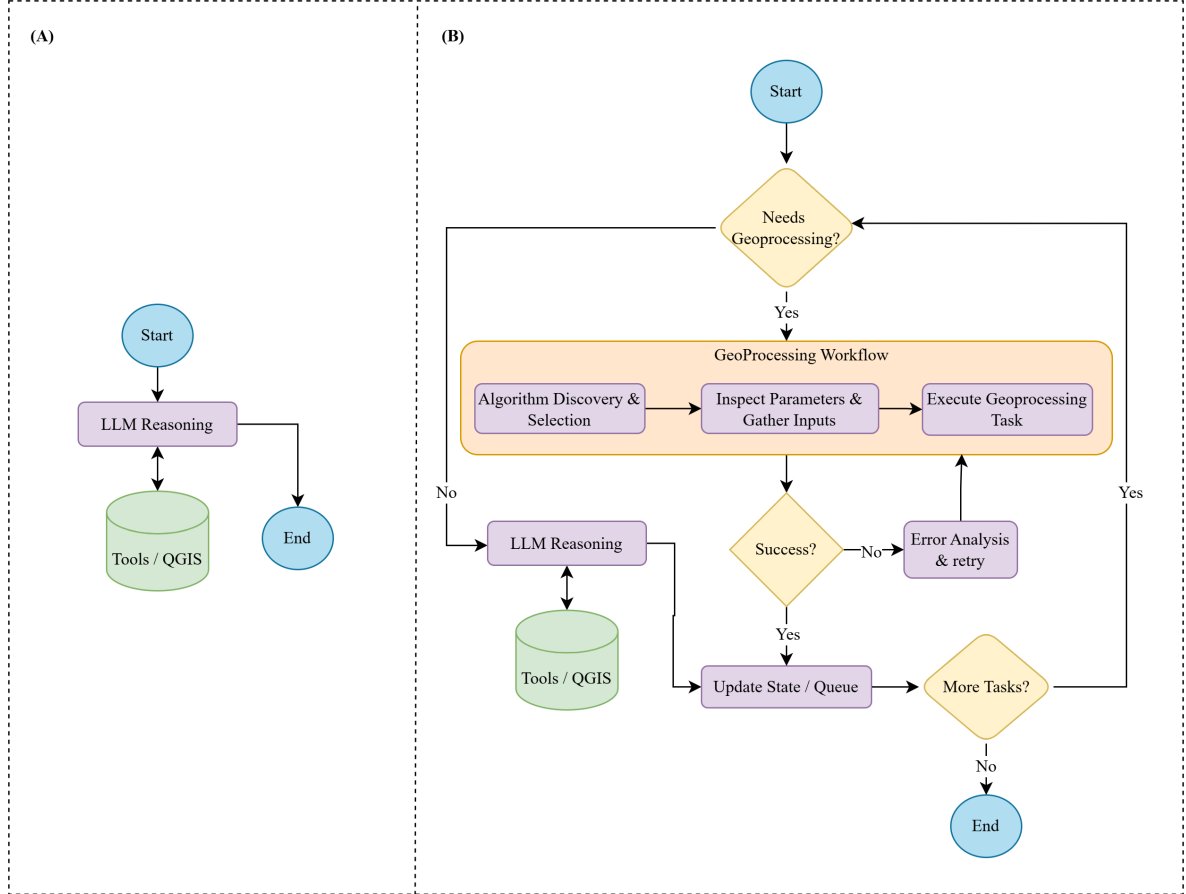


Figure 2: (A) General-mode graph: an iterative LLM reasoning loop that invokes QGIS tools as needed and returns a summarized response. (B) Processing-mode graph: the workflow engine decomposes a request into tasks and routes each through either direct LLM reasoning with tools or the geoprocessing sub-graph, with a success/error checkpoint that triggers error analysis and retry on failure.

2.3 Reliability, Concurrency, and Multi-Backend Support

To ensure operational stability and deployment flexibility, GeoAgent incorporates several core architectural safeguards. All workflow decision points—including task decomposition, routing, algorithm selection, parameter gathering, and error diagnosis—enforce Pydantic schemas via LangChain’s structured-output interface. This converts non-deterministic LLM responses into checkable objects validated against ground truth before execution.

Furthermore, GeoAgent provides a provider-agnostic backend abstraction that supports cloud providers such as OpenAI, Google Gemini, and Anthropic, alongside local inference via Ollama. The Ollama integration allows privacy-sensitive workflows to run entirely on local infrastructure without data leaving the user’s system.

Finally, to maintain user interface responsiveness during inference, heavy LLM processing runs on a background `QThread`, while a custom `@qgis_main_thread` decorator safely marshals QGIS Python API operations back onto the main thread.

3 Usage Workflow and Case Study

3.1 Demonstration Environment and Dataset

GeoAgent installs directly from the official QGIS Plugin Repository, automatically configuring required Python dependencies (LangGraph and provider SDKs) into the QGIS Python environment on first launch (Akinboyewa et al., 2025; LangChain, Inc., 2024). The plugin surfaces this workflow through a dockable panel embedded in the QGIS interface (Figure 3): a Chat Panel for entering natural-language prompts and reviewing agent responses, a Settings Panel for selecting and configuring LLM backends, and a Logs section for inspecting the step-by-step decision trace described in Section 3.3. To demonstrate end-to-end functionality, we employ the bundled, open-access demonstration dataset covering a 33×38 km mountainous study area in EPSG:32644 (UTM zone 44N). The dataset comprises a vector river network (`rivers.shp`, 96 line features) and a digital elevation model (`DEM.tif`, 30 m resolution, elevation range 87–2025 m).

3.2 Conversational Exploration and Workflow Execution

An analysis session typically opens in General mode, where users conduct preliminary exploration, such as loading layers, inspecting attribute schemas, and adjusting canvas extents through natural-language queries without navigating GUI dialogs. Behind each turn, the General-mode graph executes QGIS Python API tools dynamically, re-querying live project state to return accurate responses without relying on conversation transcript memory.

For complex spatial tasks, the user submits a single Processing-mode instruction: *“Create a 500 m buffer around the rivers, calculate slope from the DEM, and clip the slope raster with the river buffer.”* GeoAgent’s workflow engine decomposes this prompt into a three-task queue with explicit dependencies. The system selects `native:buffer` for the river network (automatically back-filling cap and join styles from algorithm defaults), invokes `native:slope` on the DEM, and passes intermediate layer outputs dynamically into `gdal:cliprasterbymasklayer`.

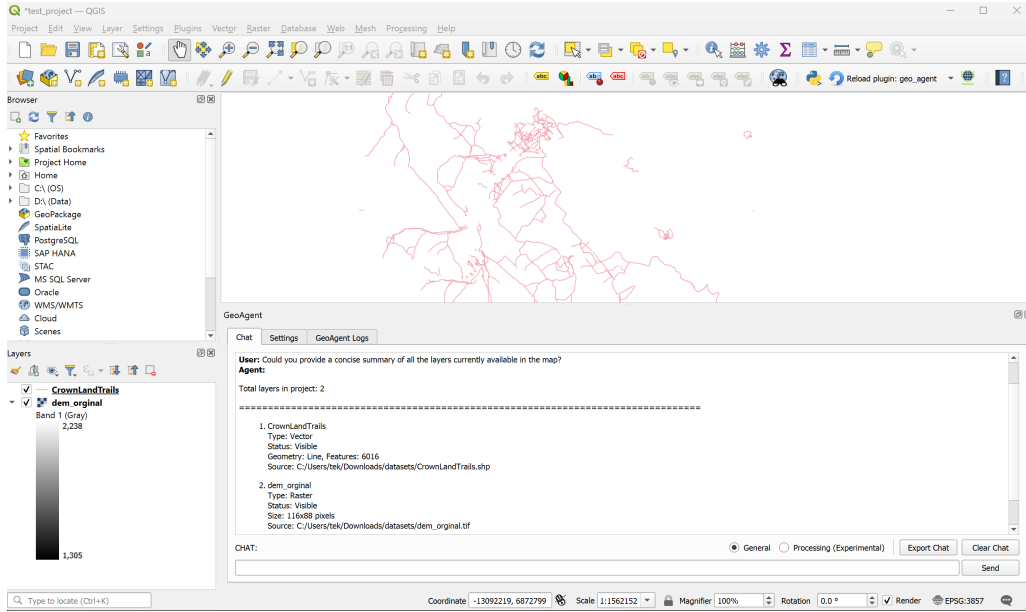


Figure 3: GeoAgent User Interface. The plugin integrates seamlessly with QGIS, providing a conversational interface for geospatial analysis. Users enter natural language requests in the input panel, view agent responses and results in the chat history, configure LLM backends and parameters in the settings, and monitor execution logs for transparency.

Upon completion, the clipped slope raster is loaded and symbolized in the active project, highlighting rapid-runoff steep slopes versus flat accumulation zones near waterways.

3.3 Error Recovery and Reproducibility

When a workflow fails, for instance, if a user attempts to clip a raster using unbuffered line features where a polygon mask is required, GeoAgent’s error-analysis node captures the exception traceback. The LLM diagnoses the geometry mismatch, adds the failed algorithm to an exclusion list, and executes a steered retry using corrected parameters or provides actionable troubleshooting suggestions in the chat panel.

To maintain scientific auditability despite LLM non-determinism, GeoAgent records all executed algorithm identifiers, full parameter dictionaries, and decision reasoning in a dedicated Logs tab, allowing exact methodological replication regardless of natural-language phrasing.

4 Discussion and Future Work

4.1 Comparison with Existing LLM–GIS Systems

GeoAgent sits within a rapidly evolving landscape of LLM–GIS integrations, summarized in Table 1. Two key architectural choices distinguish GeoAgent from existing tools. First is the execution mechanism: while systems such as GIS Copilot (Akinboyewa et al., 2025), ChatGeoAI (Mansourian and Oucheikh, 2024), and LLM-Geo (Li and Ning, 2023) rely on generating free-form Python or PyQGIS code, GeoAgent configures invocations of existing, tested algorithms directly from the host GIS registry. While code generation offers theoretical expressiveness, non-deterministic LLM output introduces verification challenges and silent runtime bugs (Ouyang

et al., 2025). In contrast, GeoAgent trades open-ended code generation for strict verifiability—validating algorithm existence and parameter schemas before execution while preserving complete access to hundreds of curated tools in the QGIS processing ecosystem.

Second is deployment flexibility and workflow orchestration. GeoAgent and ChatGeoAI (Mansourian and Oucheikh, 2024) are among the few systems providing fully local, privacy-preserving inference via Ollama, enabling institutions with strict data governance to deploy AI assistants without cloud data transmission. Furthermore, multi-step task chaining paired with automated error diagnosis and steered retries directly within desktop QGIS remains unique to GeoAgent, bridging the gap between conversational exploration and robust workflow automation.

Table 1: Comparison of GeoAgent with existing LLM-GIS systems.

System	Integration	Execution Mechanism	Multi-Step	Error Recovery	Local LLM
LLM-Geo (Li and Ning, 2023)	Standalone Python	Generated code	Yes	No	No
GeoGPT (Zhang et al., 2024)	Standalone	Tool chaining	Yes	No	No
GeoJSON Agents (Luo et al., 2026)	Standalone	Function calling / code	Yes	No	No
GIS Copilot (Akinboyewa et al., 2025)	QGIS plugin	Generated PyQGIS code	Partial	No	No
ChatGeoAI (Mansourian and Oucheikh, 2024)	PyQGIS-based	Generated PyQGIS code	No	Limited	Yes
IntelliGeo (IntelliGeo, 2024)	QGIS plugin	Workflow assistance	No	No	No
QChatGPT (QChatGPT, 2024)	QGIS plugin	Chat only	No	No	No
QGIS MCP (QGIS MCP, 2025)	External client	Remote commands	Client	No	No
GeoAgent (this work)	QGIS plugin	Configured registry invocations	Yes	LLM retry	Yes

4.2 Limitations and Future Work

Despite these advantages, several limitations remain. First, because GeoAgent configures registry algorithms based on catalog metadata, tools with sparse descriptions are harder for the lexical prefilter to discover. Second, processing operations currently execute without an explicit user approval dialog, meaning long-running tasks are launched immediately upon parameter assembly. Finally, workflows halt at the first unrecoverable task failure rather than dynamically re-planning around errors.

Future developments will focus on four key enhancements: (1) implementing an interactive parameter confirmation dialog to allow user review prior to algorithm execution; (2) incorporating Retrieval-Augmented Generation (RAG) over full algorithm documentation to improve discovery of niche tools; (3) enabling workflow export to serialize successful multi-step executions directly

into native QGIS graphical models for full operational reproducibility; and (4) supporting dynamic workflow re-planning to gracefully bypass or substitute failed steps.

5 Data and Code Availability

GeoAgent is free and open-source software released under the MIT license. The source code is developed openly at <https://github.com/iamtekson/GeoAgent>, and the plugin is distributed through the official QGIS Plugin Repository at https://plugins.qgis.org/plugins/geo_agent/. The version described in this paper is GeoAgent v0.5.2; a snapshot of the exact version is archived at Zenodo under DOI <https://doi.org/10.5281/zenodo.23048185>. GeoAgent requires QGIS 3.2 or newer and supports QGIS 4.

The demonstration dataset used in Section 3 (river network and digital elevation model) is bundled with the source repository under `paper/demo_dataset/`. It is derived from openly available geospatial data and is packaged solely for software demonstration and validation; it carries no usage restrictions beyond attribution of the repository.

Readers reproducing the case study will additionally need access to an LLM backend. All four supported backends are interchangeable for this purpose; the Ollama path requires no account or API key and runs entirely on the reader’s machine.

6 CRediT Author Contributions

Tek Kshetri: Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft, Writing – review & editing.

Rabin Ojha: Software, Validation, Writing – review & editing.

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Conflicts of Interest

The authors declare no conflicts of interest. This work received no external funding.

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