

Exploring Retrieval-Augmented Code Generation for Procedural Modelling in Houdini

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Motivation / Problem

Motivation

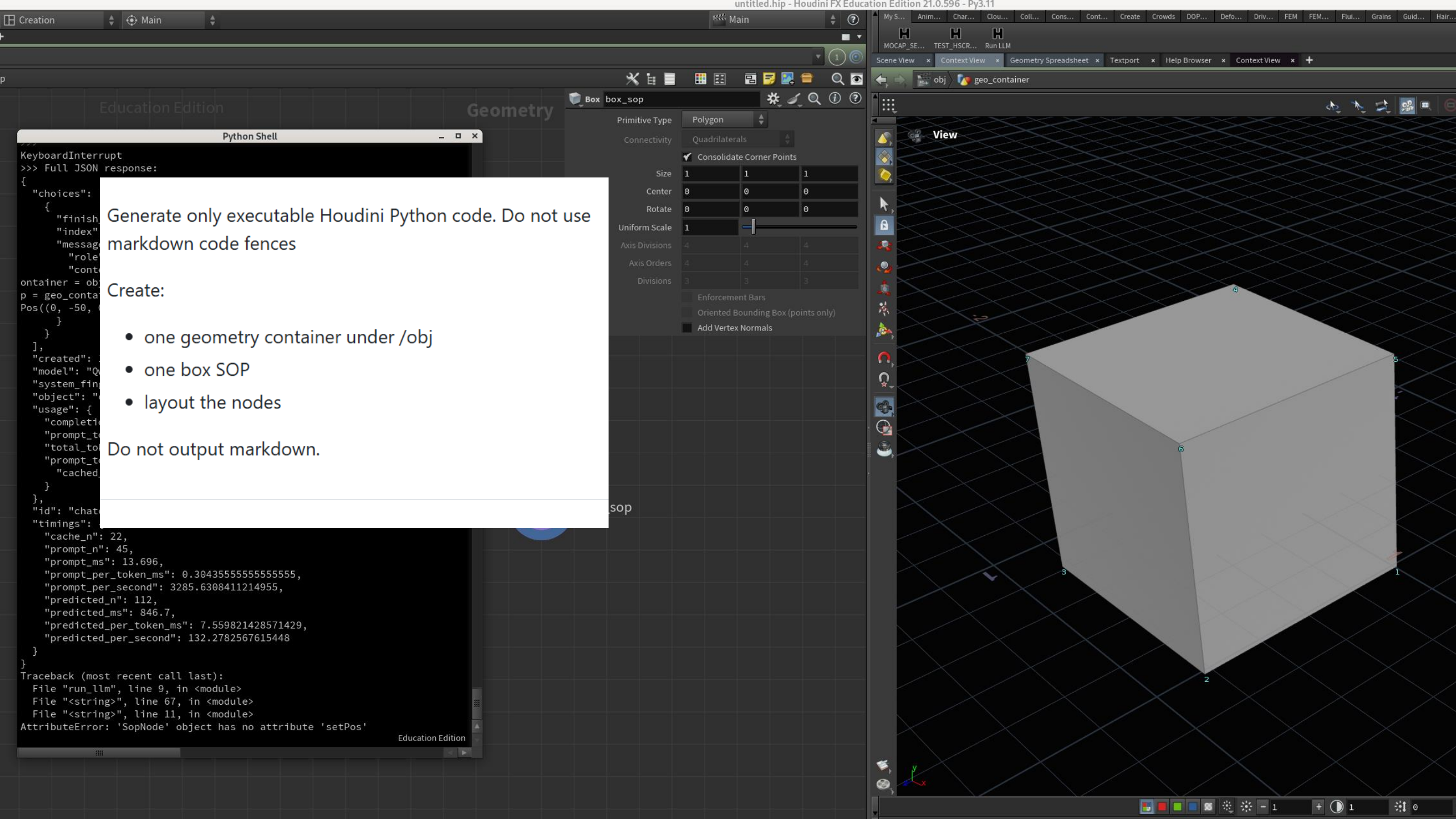
- Use natural language to support procedural modelling tasks
- Investigate what role AI can realistically play inside a PCG workflow

Initial Prototype

- Natural language → LLM-generated Houdini Python
- Local Qwen2.5-Coder-7B as the primary generator
- Simple tasks worked, but more complex tasks exposed limitations

Problem Identified During Development

- Failures were often related to missing Houdini-specific procedural knowledge
- Prompt engineering became increasingly solution-specific
- These observations motivated the introduction of RAG



Generate only executable Houdini Python code. Do not use markdown code fences

Create:

- one geometry container under /obj
- one box SOP
- layout the nodes

Do not output markdown.

Generate only executable Houdini Python code.

Do not use markdown code fences. Do not explain your solution.

Create:

- one geometry container under /obj

Create the following SOP network:

Grid ↓

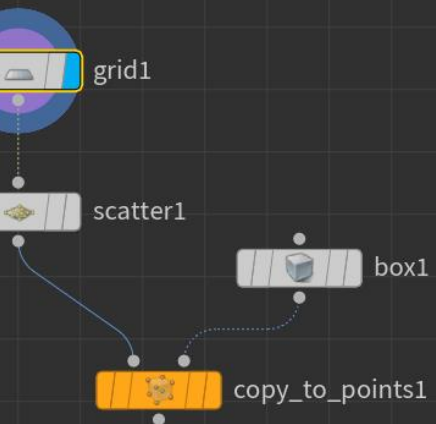
Scatter ↓

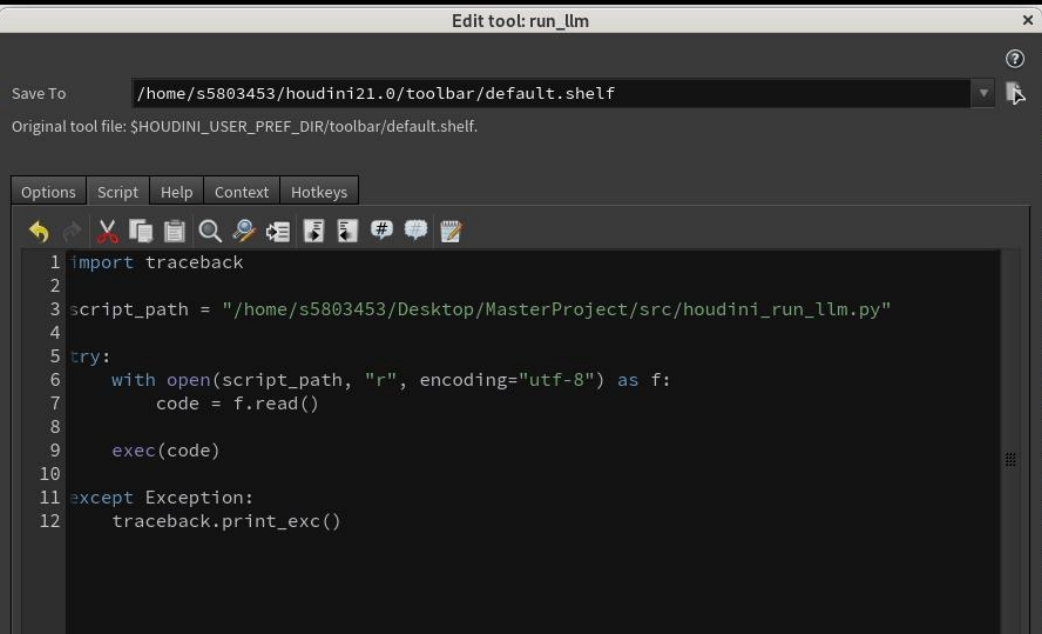
Copy to Points

Copy one Box SOP onto the scattered points.

Layout the nodes.

Output executable Python only.





Generate only executable Houdini Python code. Do not use markdown code fences. Do not explain your solution.

Create these SOP nodes inside one geometry container: Create:

- one geometry container under /obj
- one Box SOP
- one Grid SOP
- one Scatter SOP
- one Copy to Points SOP

You must connect them using exactly these statements:

```
scatter.setInput(0, grid) copytopoints.setInput(0, box) copytopoints.setInput(1, scatter)
```

Then set: `copytopoints.setDisplayFlag(True)` `copytopoints.setRenderFlag(True)`

Layout the nodes.

Output executable Python only.

From Direct Generation to RAG

Direct Generation

- Simple node tasks succeeded
- Copy to Points exposed Houdini-specific failures
- Missing nodes, reversed inputs and wrong display flags

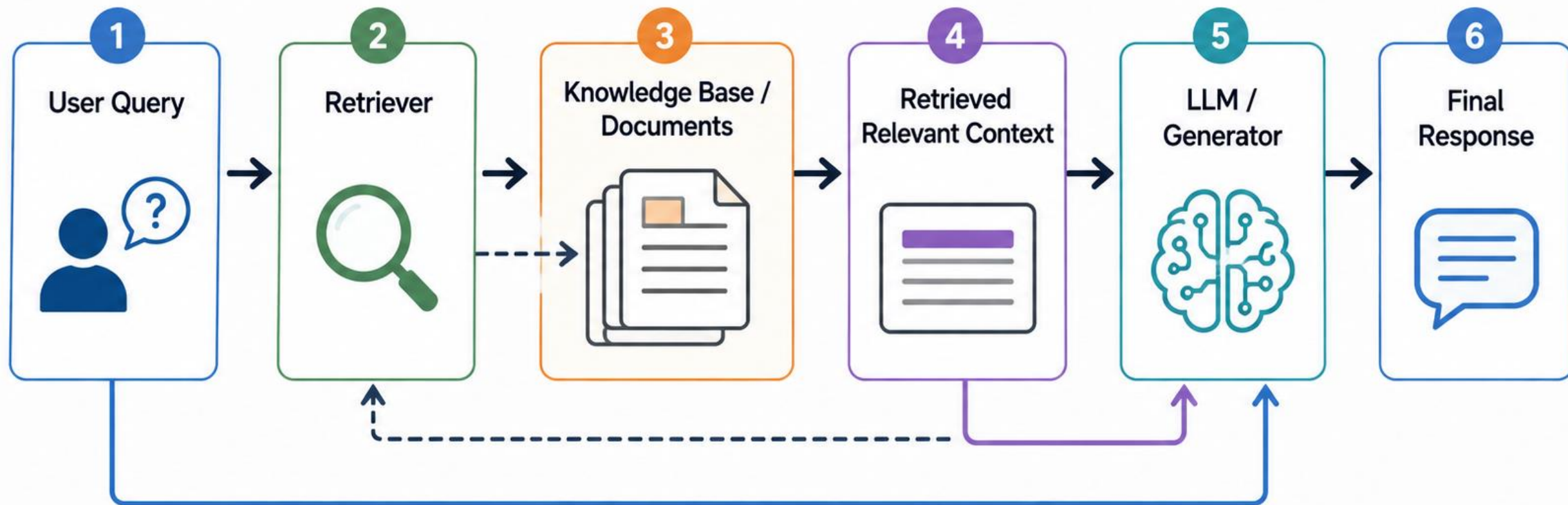
Prompt Engineering

- Increasingly explicit prompts eventually succeeded
- Connection order and final display node had to be specified
- The prompt became close to a procedural recipe

RAG

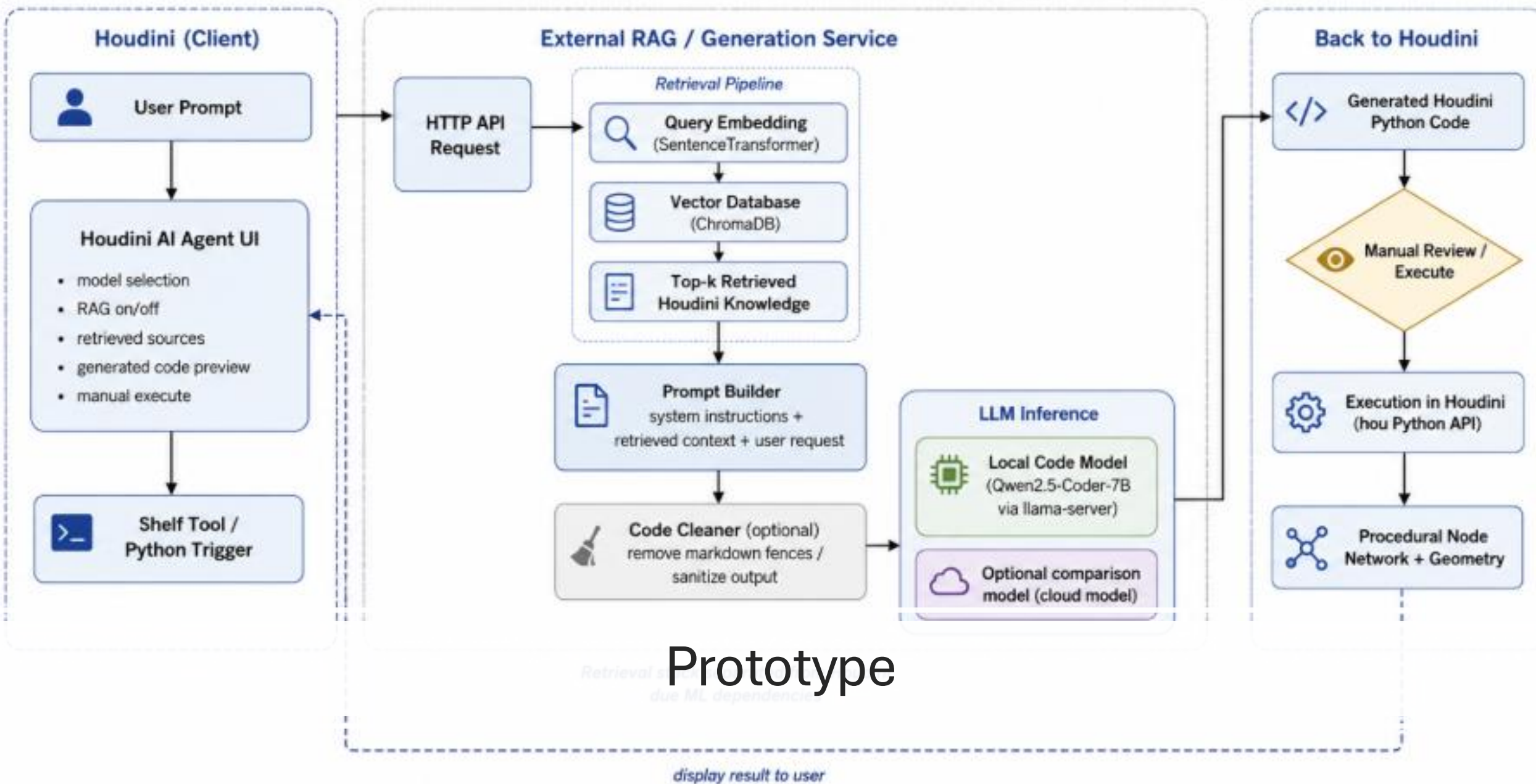
- Move reusable Houdini knowledge outside the user prompt
- Retrieve relevant procedural patterns when needed
- Reuse verified domain knowledge across tasks

Retrieval-Augmented Generation (RAG)



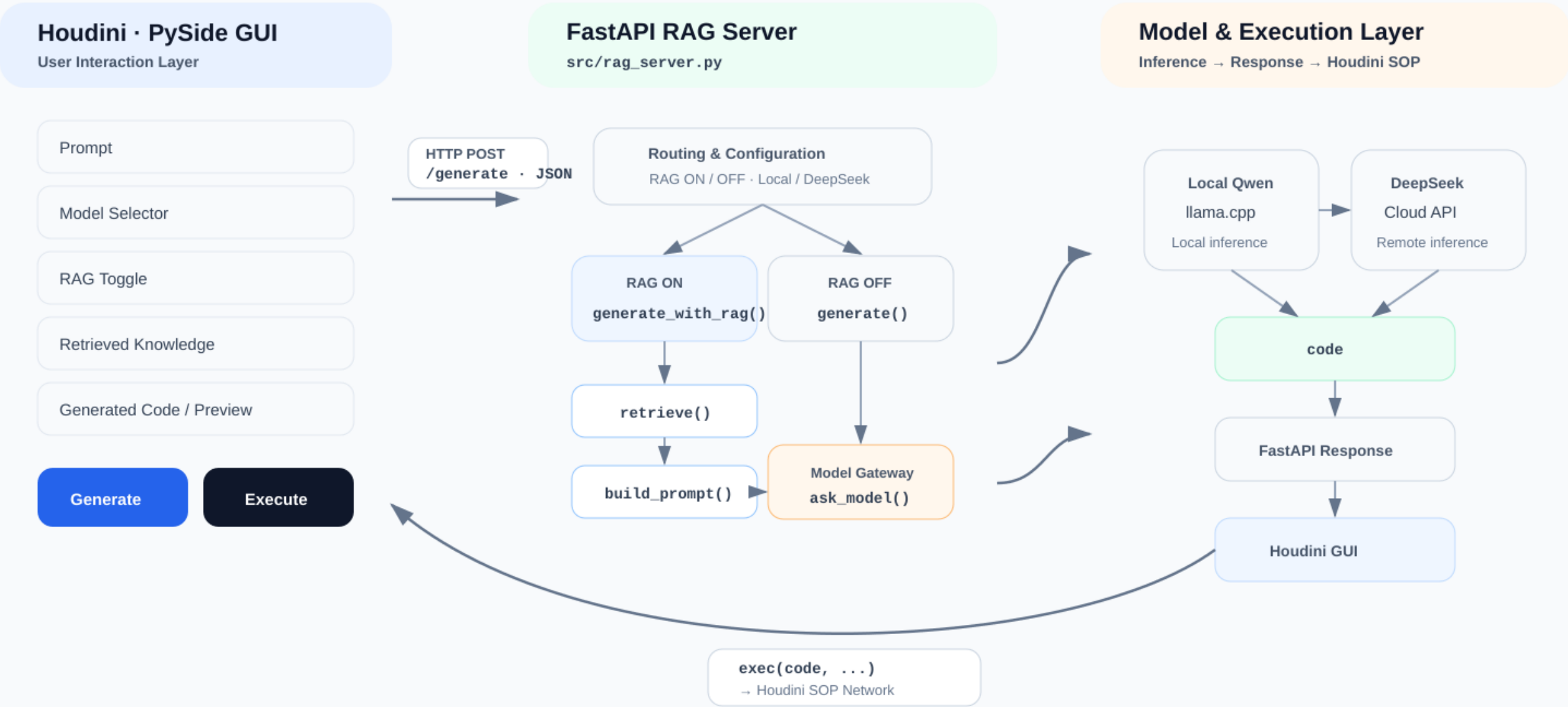
RAG adds external knowledge at inference time without retraining the model.

System Architecture of the Houdini AI Agent Prototype



Houdini AI Code Generation · RAG Workflow

PySide GUI → FastAPI RAG Server → Retrieval / Model Routing → Code Execution



RAG Is Also an Engineering Problem

Knowledge Quality

- Tutorial examples contained irrelevant process and layout code
- Cleaner document structure improved retrieval ranking
- procedural_staircase_code_rag.md: 0.5122 → 0.4541

Chunking

- Complete spiral examples created long contexts and high token cost
- Split into core / railing / baluster knowledge

Query Design

- Full generation prompts could distort semantic retrieval
- Retrieval query and generation prompt were separated
- spiral_core.md: 0.5663 → 0.2631 with a concise semantic query

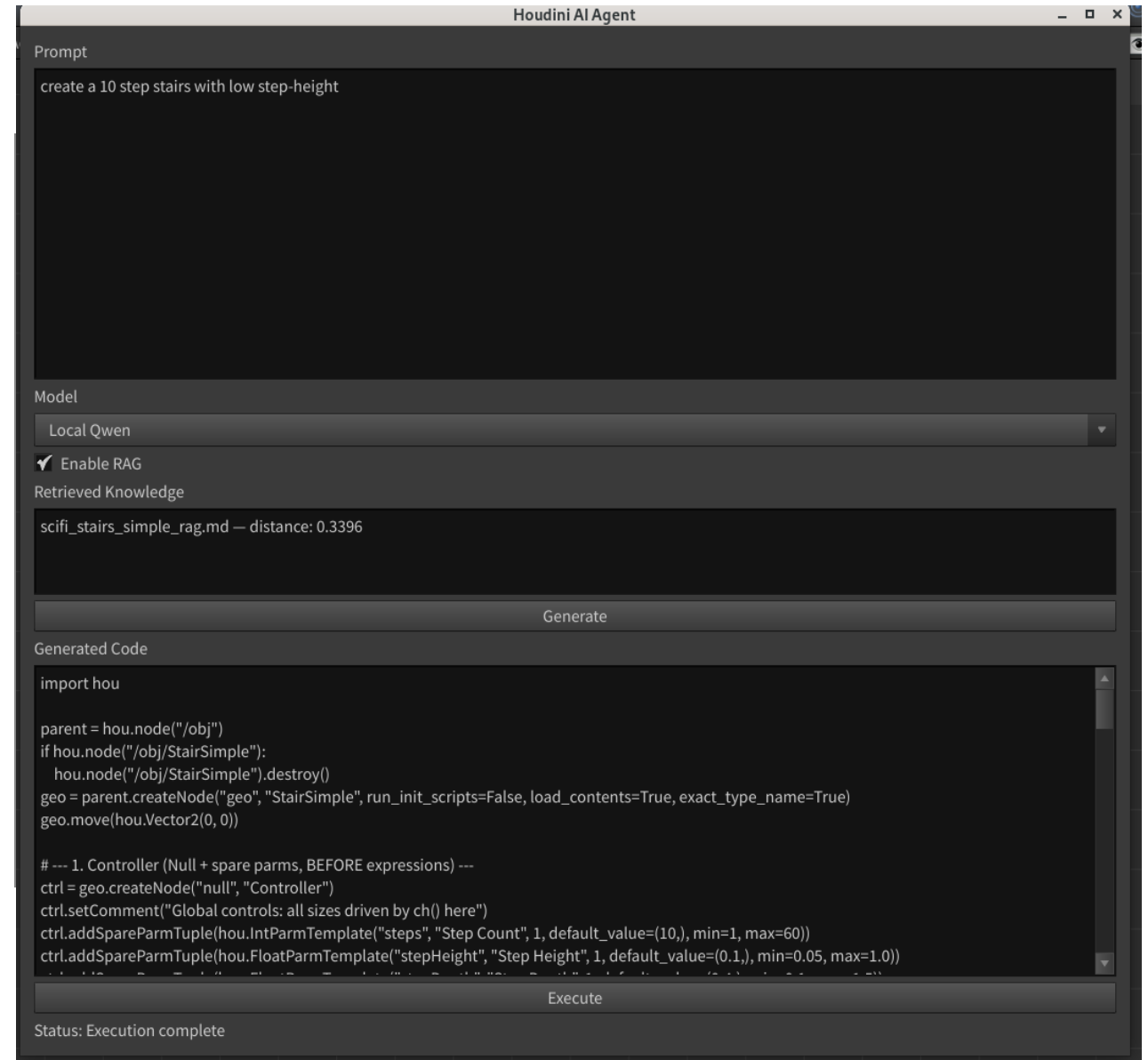
Top-k

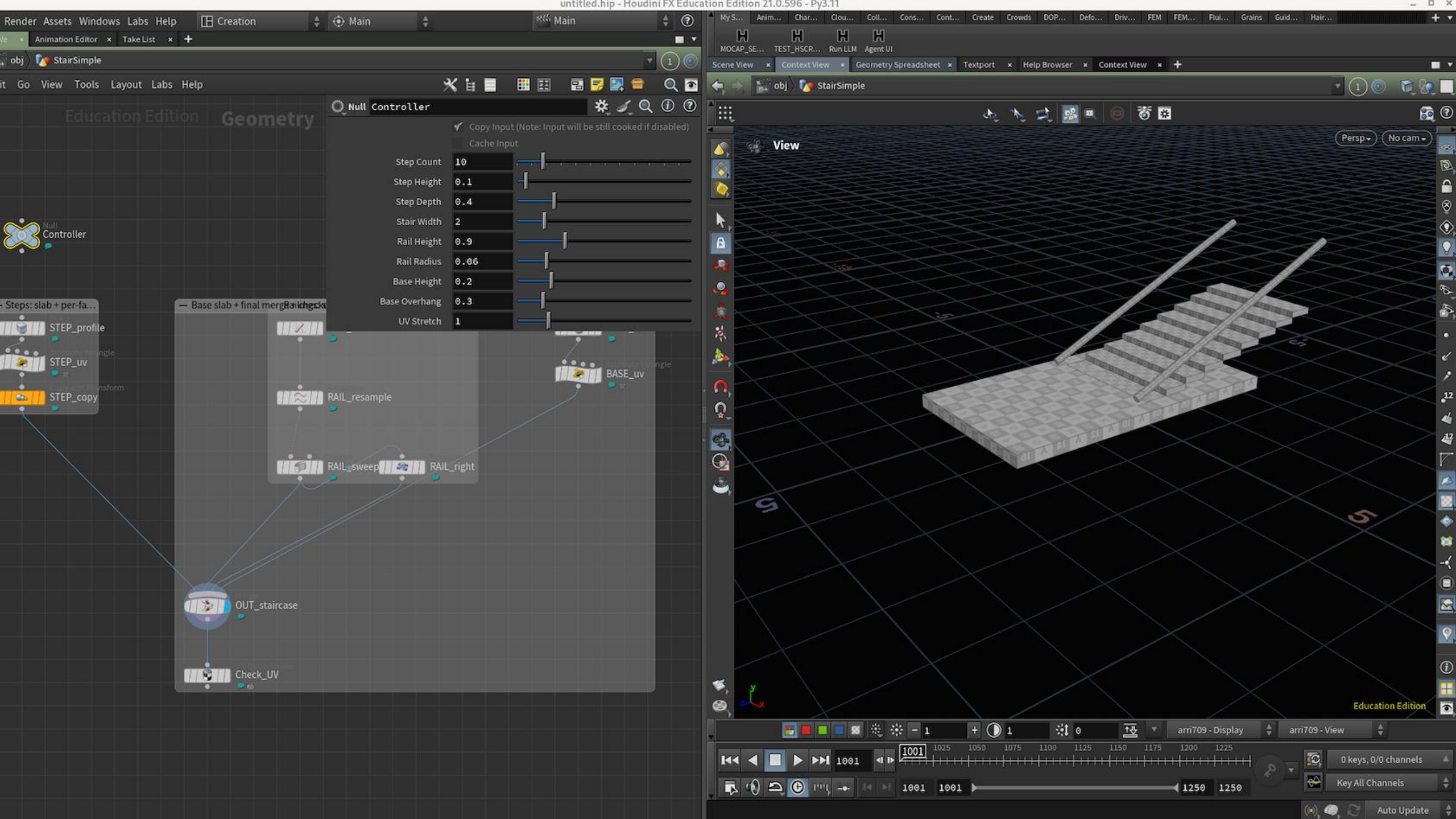
- Controls procedural coverage versus context cost
- top-k = 1: core structure
- top-k = 3: additional railing and baluster components

Key Findings

Natural language can modify existing procedural parameters

- Maps user intent to an existing procedural control
- The requested staircase step count and height was changed successfully

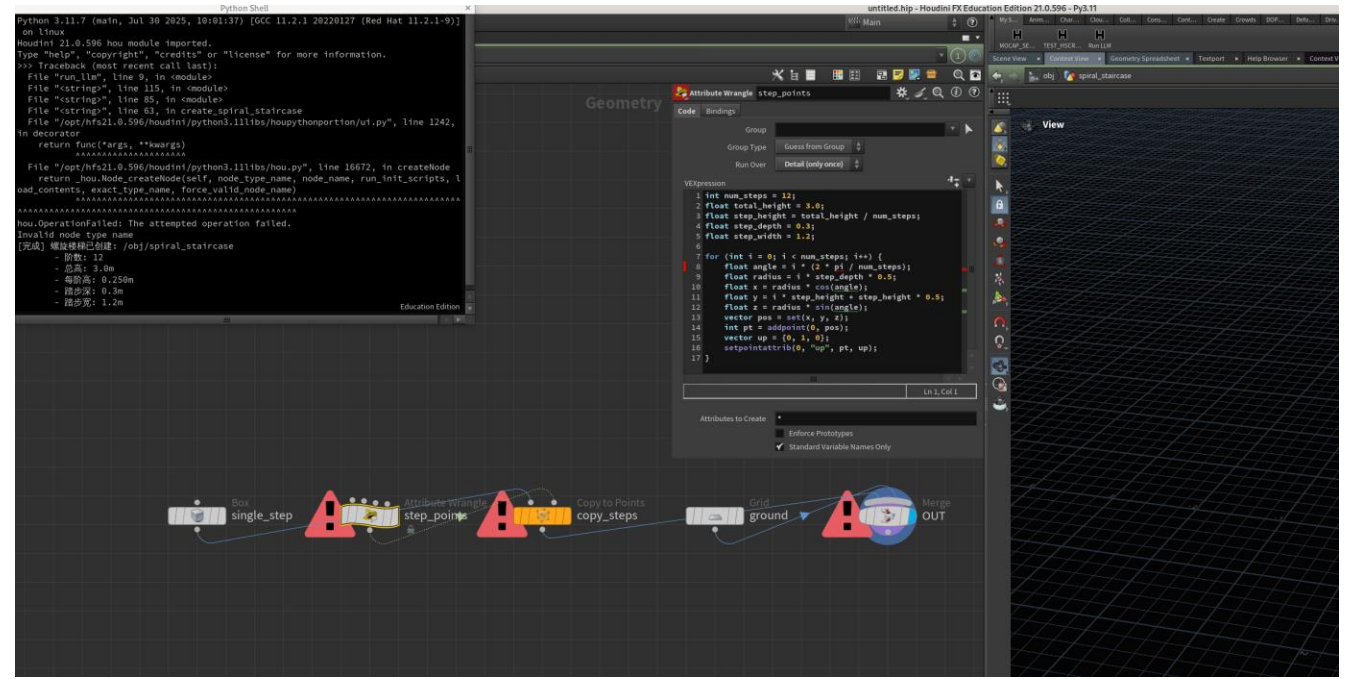




Key Findings

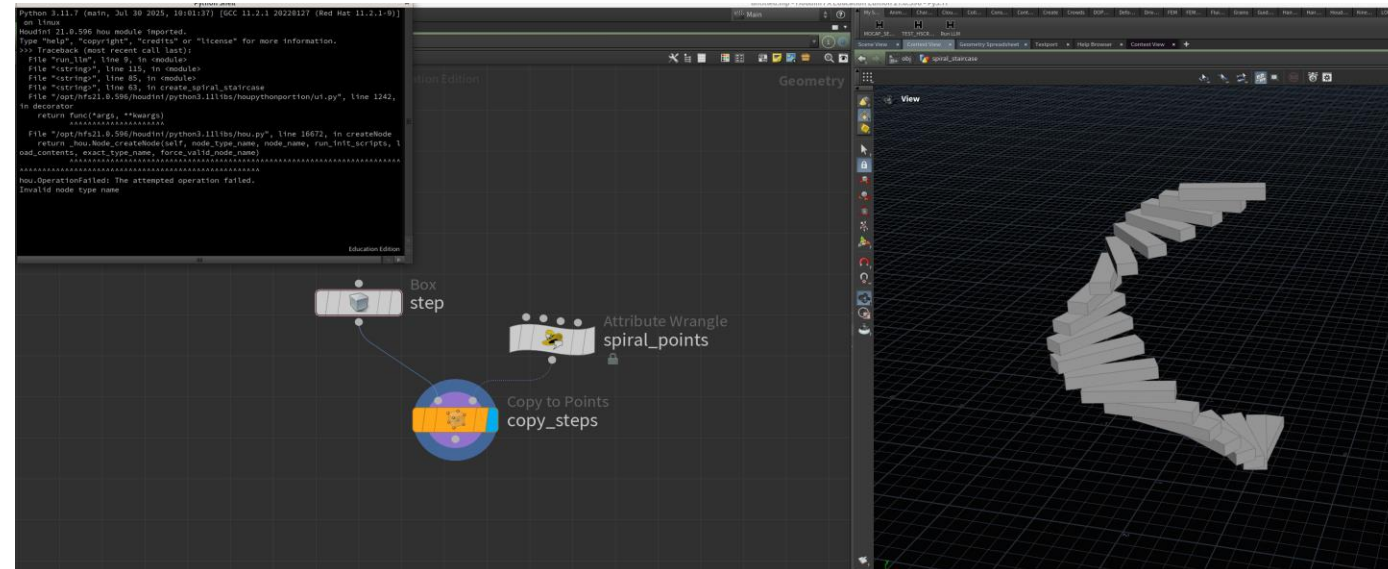
RAG can provide reusable Houdini-specific patterns

- Copy to Points benefited from retrieved connection knowledge
- Straight staircase reused an existing procedural structure



Complex composition still depends on model capability

- Spiral tasks required several spatial and orientation relationships
- Local and cloud models failed in different ways



Implications and Future Work

Implications

- AI can act as an interface to existing procedural systems
- Current prototype: natural language → generated Houdini code
- Observed: reuse and parameter modification of procedural patterns
- Potential direction: module selection and parameter configuration

Future Work

- Reranking retrieved candidates before final top-k selection
- Model-specific RAG configurations for small and large models
- Multi-agent decomposition: planning, retrieval, coding and verification
- Error-driven repair using Python / VEX / Houdini feedback
- Visual or geometric validation
- Structured PCG knowledge: modules, parameters and interfaces

Demo

Live Workflow

- Enter a natural-language request
- Enable RAG
- Inspect retrieved knowledge
- Generate Houdini Python
- Review and execute
- Inspect the SOP network and geometry

<https://vimeo.com/1218752953?share=copy&fl=sv&fe=ci>