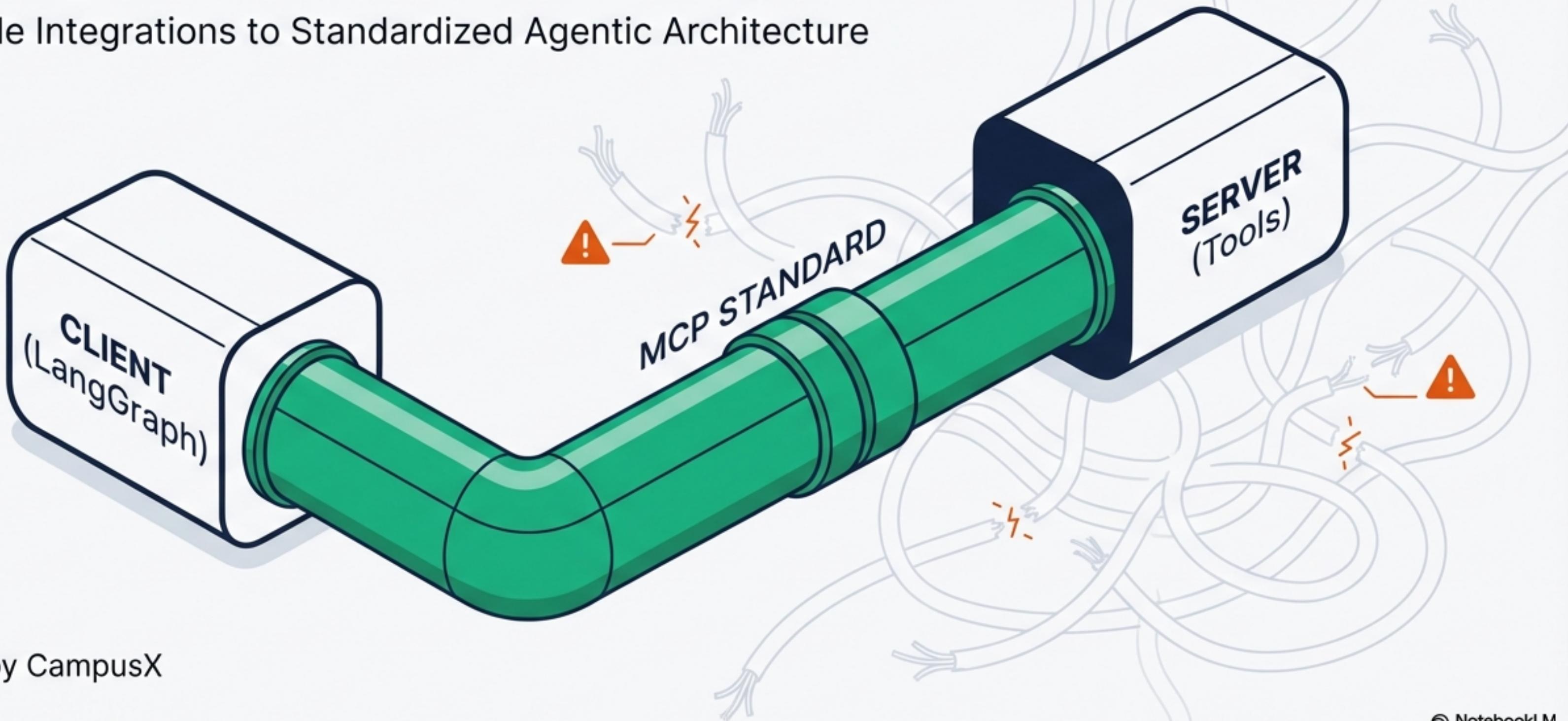


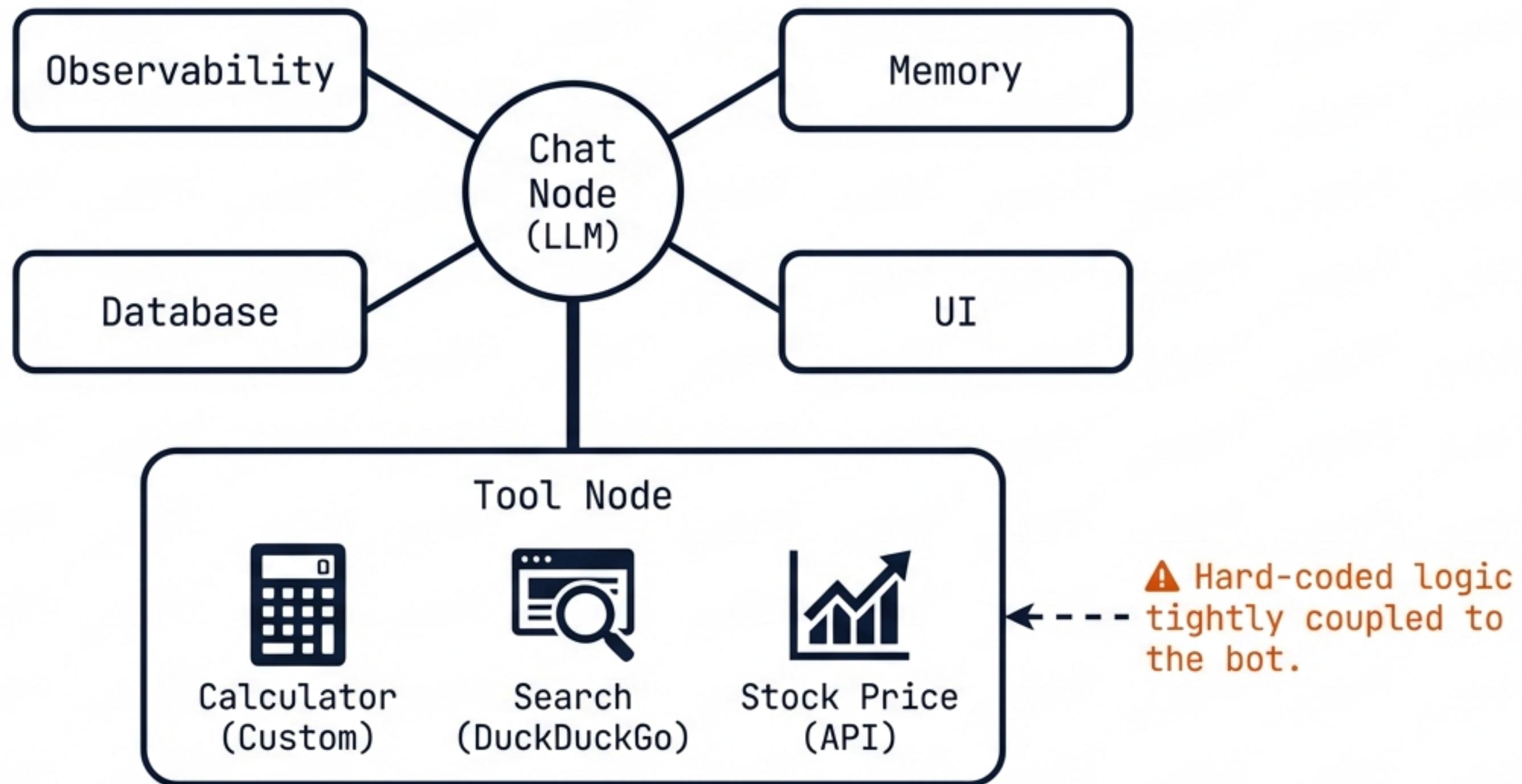
Escaping the Tool Trap: Building MCP Clients in LangGraph

From Brittle Integrations to Standardized Agentic Architecture



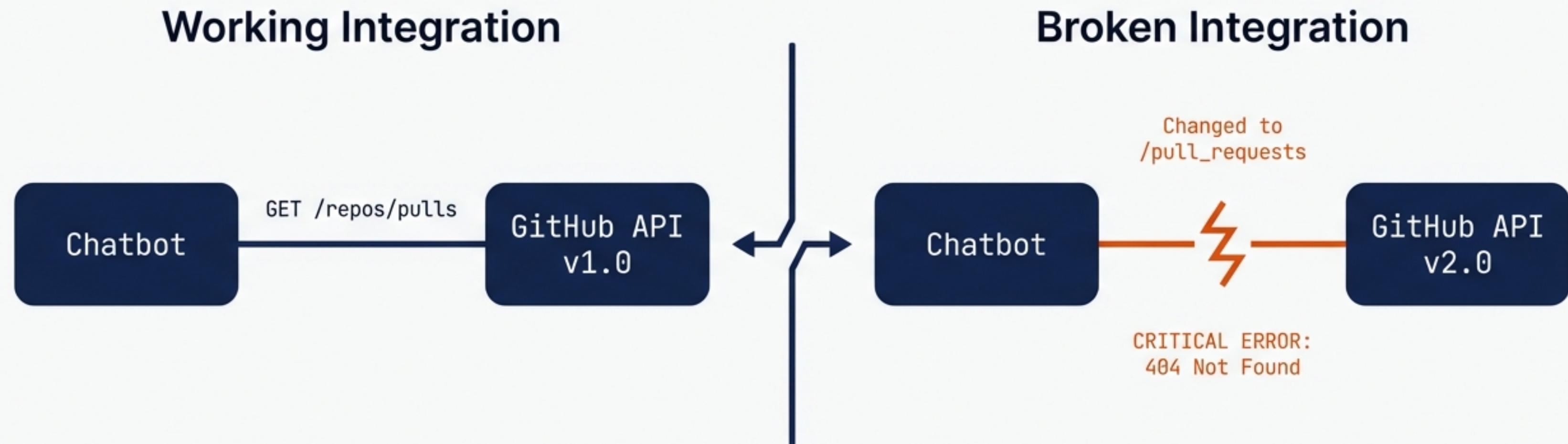
Presented by CampusX

The Status Quo: A Capable but Flawed Agent



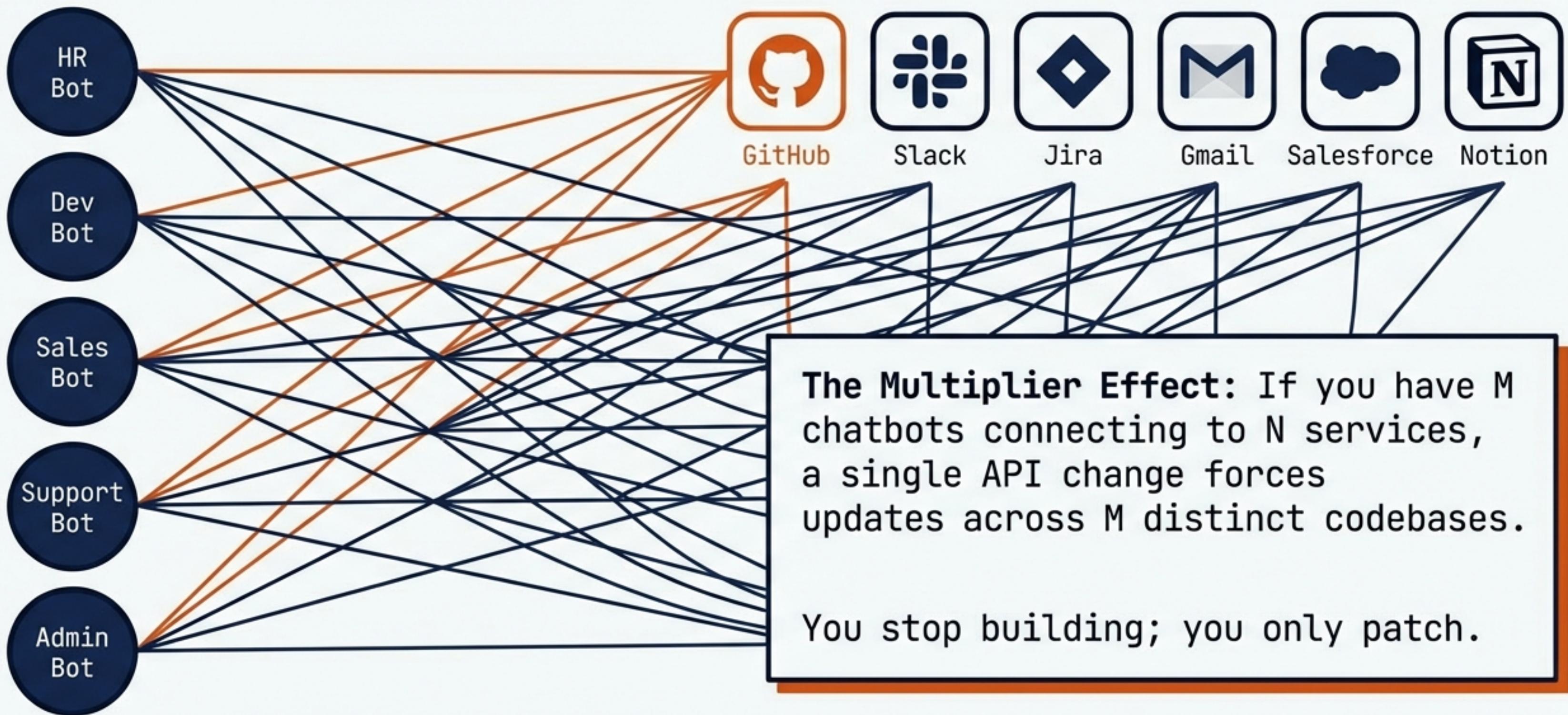
Current State: We have a functional agent with memory and persistence. However, the method of connecting tools is manual and brittle.

The Problem: Brittle Integrations



The GitHub Scenario: When a service provider updates their API, hard-coded tools inside the chatbot crash instantly. Constant monitoring is required.

The Maintenance Nightmare: The $N \times M$ Problem



The Solution: Model Context Protocol (MCP)

Client Side (The Chatbot)

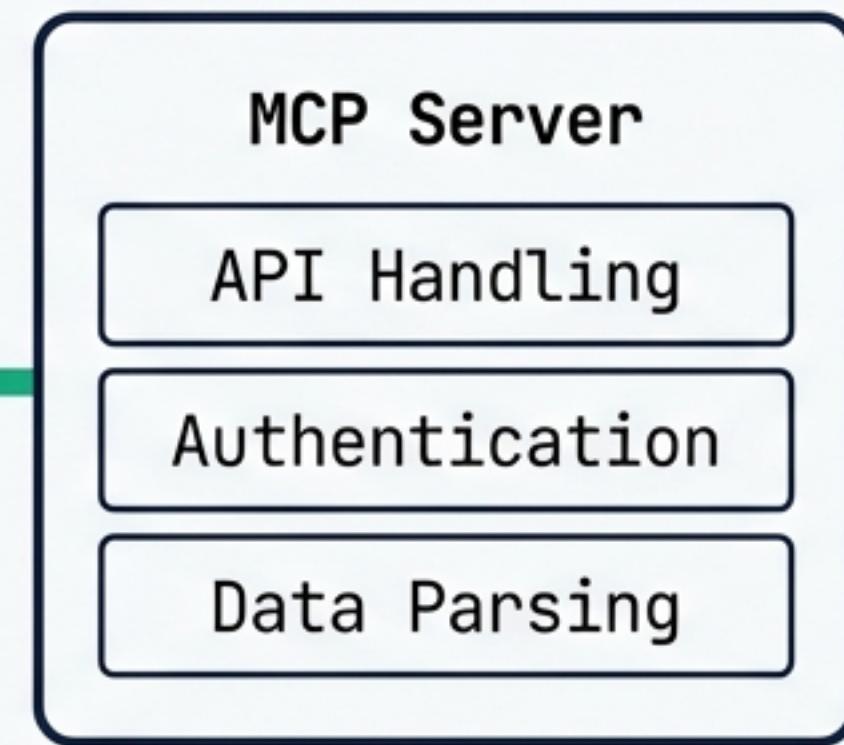


Stable. Zero
Code Changes.

MCP Standard Protocol



Server Side (The Logic)



Handles Updates &
Heavy Lifting.

Separation of Concerns: The Client only asks "What can you do?". The Server handles "How I do it." If the API changes, only the Server updates.

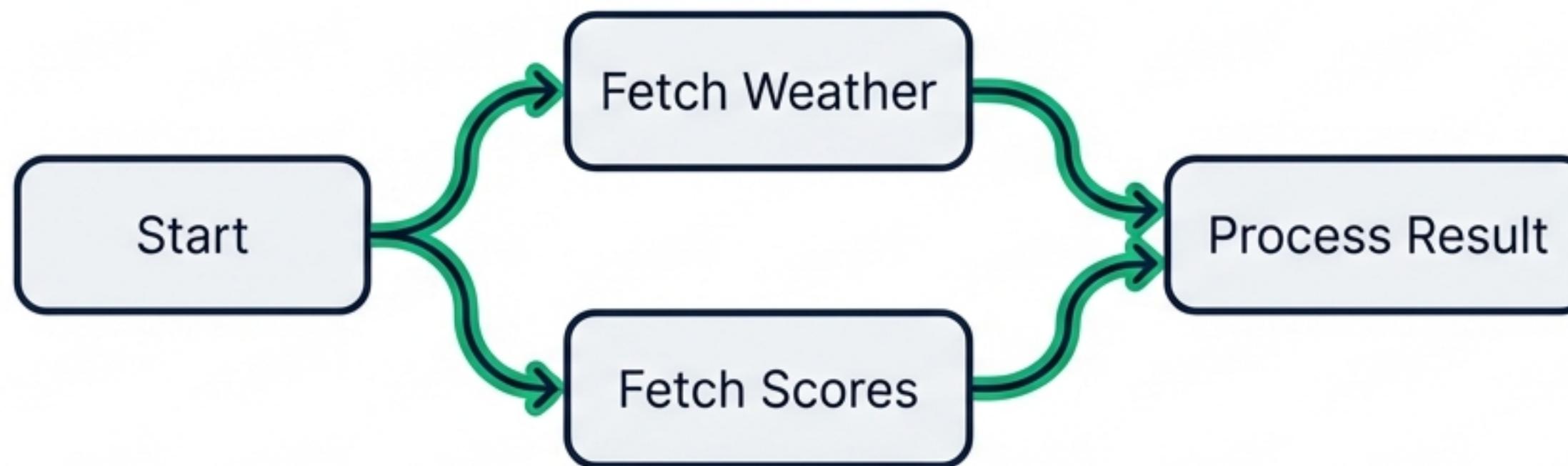
The Prerequisite: Shifting to Async

Synchronous Flow (Greyed Out)



Constraint: langchain-mcp-adapters is an **Async-only** library.

Asynchronous Flow (Highlighted Blue)



Action: We must refactor LangGraph from `invoke` to `ainvoke`.

Benefit: Parallel execution and non-blocking I/O.

Refactoring for Async: The Code Transformation

Code Diff

Before (Sync)

```
def main():
    result = graph.invoke(inputs)
    print(result)
```

```
# Node Definition
def chat_node(state):
    return llm.invoke(state)
```

After (Async)

```
import asyncio

async def main():
    result = await graph.invoke(inputs)
    print(result)
```

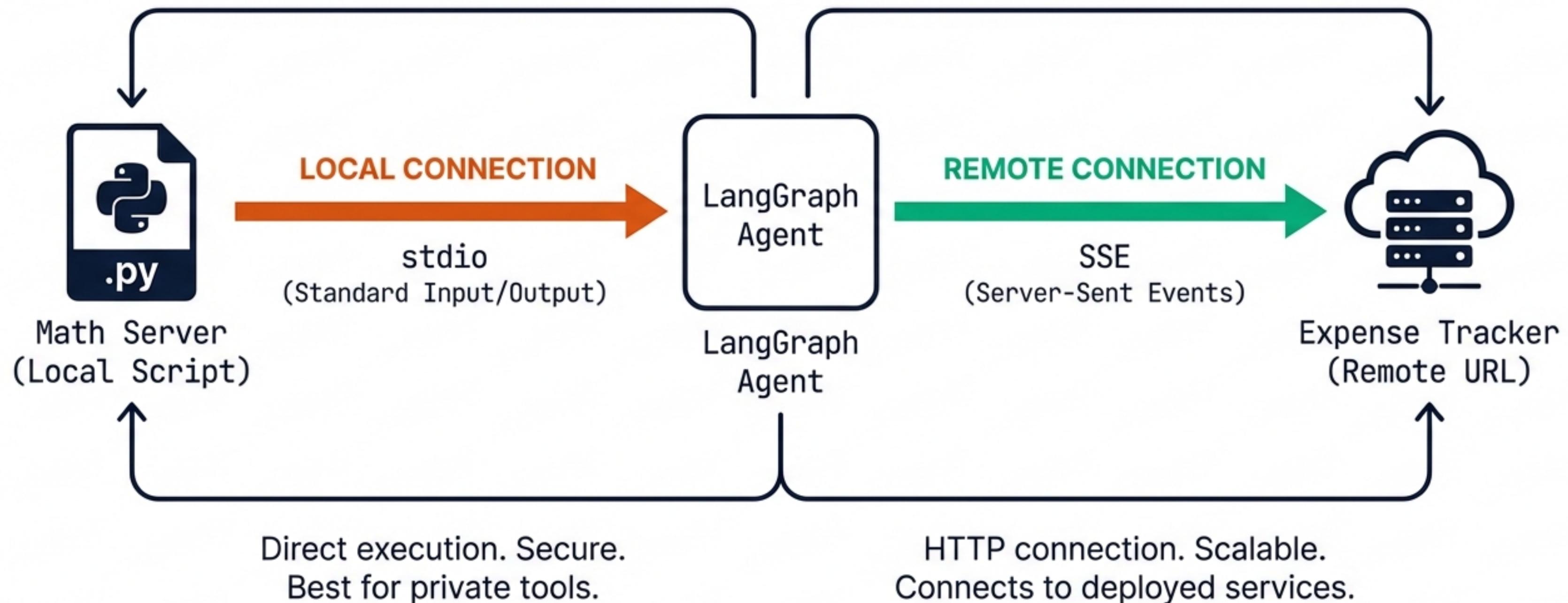
```
# Node Definition
async def chat_node(state):
    return await llm.invoke(state)
```

Note: LangGraph's built-in ToolNode is natively async compatible. Only custom nodes need manual refactoring.

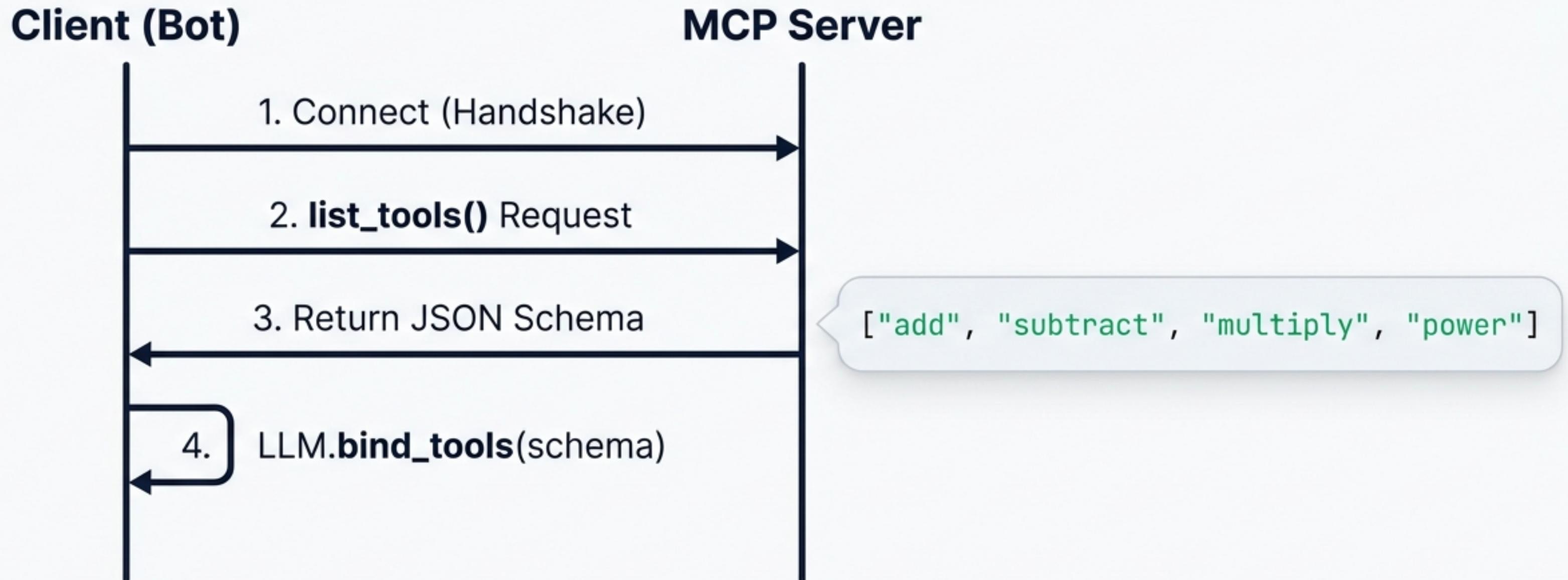
Implementation: The Multi-Server MCP Client

```
from langchain_mcp_adapters.client import MultiServerMCPClient ←  
The adapter library that  
bridges LangGraph and  
MCP.  
  
# Initialize the Client  
client = MultiServerMCPClient(  
    servers={  
        "math_server": {  
            "command": "python",  
            "args": ["path/to/math_server.py"],  
            "transport": "stdio"  
        }  
    }  
)  
  
# Dynamic Tool Binding  
tools = await client.get_tools() ←  
llm_with_tools = llm.bind_tools(tools)  
Defining the server config.  
No tool logic here.  
Runtime discovery. The  
bot asks the server what  
it can do.
```

Connection Protocols: Local vs. Remote

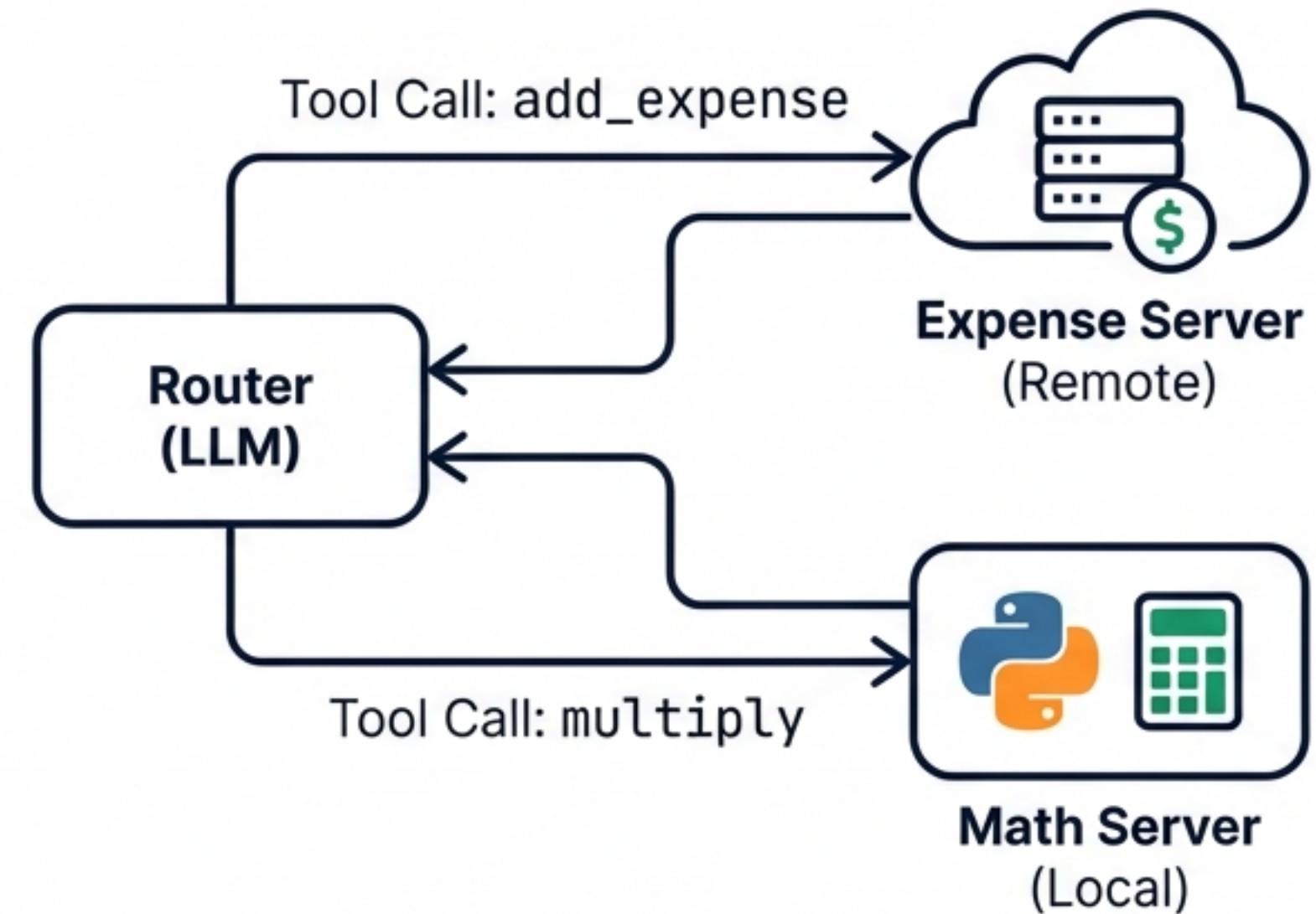
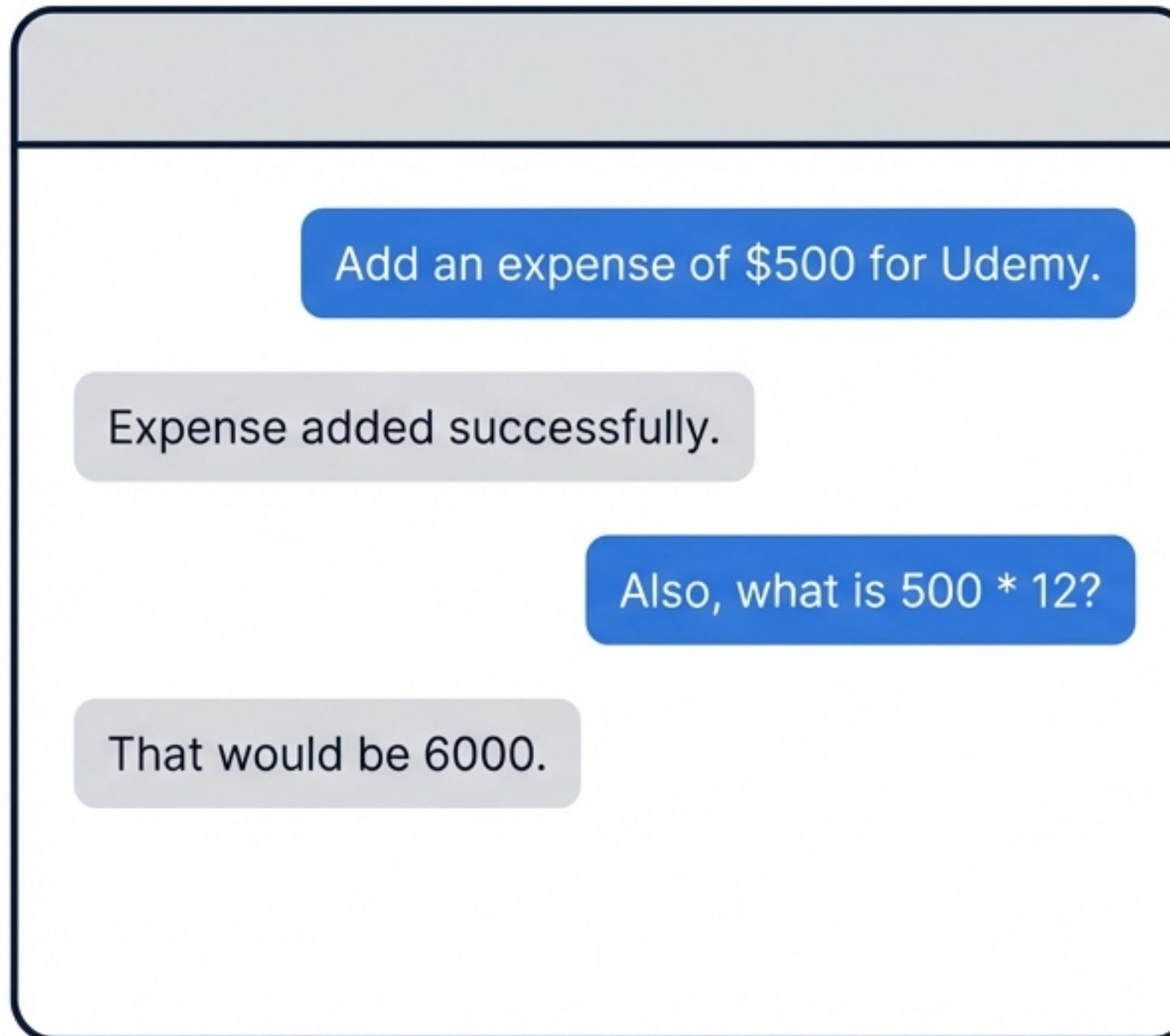


Dynamic Discovery: ‘What Can You Do?’



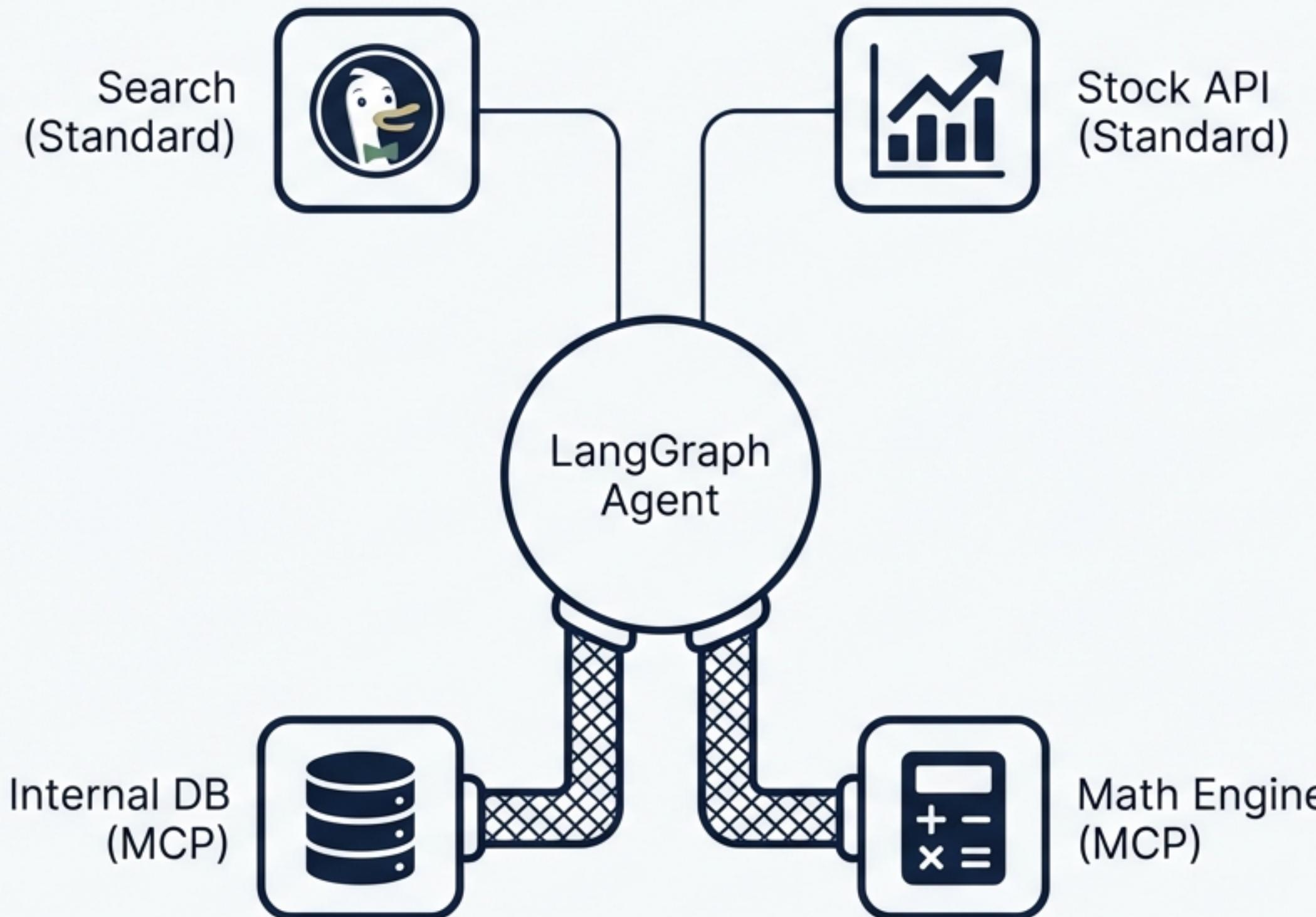
Key Insight: Zero Manual Definition: The bot adapts instantly. If the Server adds “Square Root” tomorrow, the Client supports it automatically.

Multi-Server Architecture in Action



Unified Interface. The LLM intelligently routes queries to the correct MCP server based on the discovered schemas.

Hybrid Architecture: Best of Both Worlds



Flexibility: Keep stable, simple tools as standard integrations. Move complex, evolving, or proprietary integrations to MCP servers.

Real-World Friction: The Sync/Async Conflict

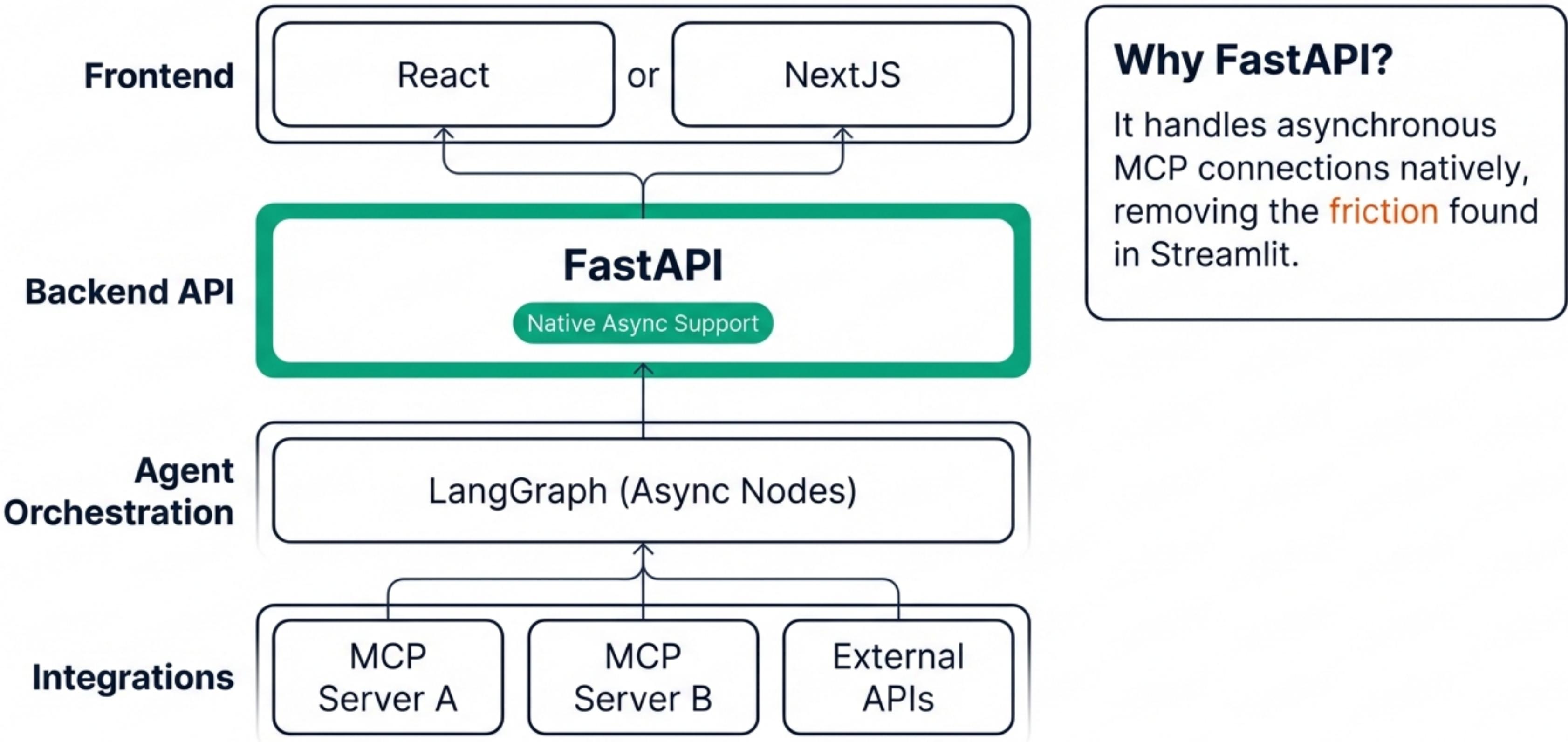


Workaround

```
asyncio.run(main())
AIOSQLite (Async Database)
```

The Hack: Bridging the gap requires forcing an async event loop within Streamlit and migrating standard SQLite to AIOSQLite. Functional, but not optimal.

The Production Stack Recommendation



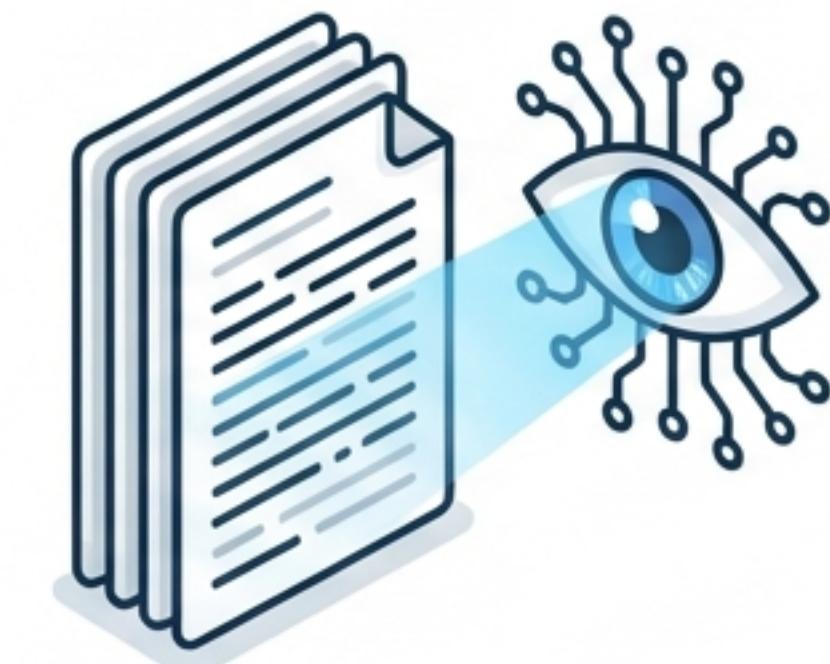
Summary & What's Next

[✓] Basic Chat & Memory

[✓] Web Search & Tools

[✓] Standardized Integrations (MCP)

[□] Internal Knowledge (RAG)



Retrieval Augmented
Generation

Achievement Unlocked: We have decoupled our agent from its tools, solving the maintenance headache. Next, we teach the agent to KNOW things using RAG.