

Rainy Day Stocks

Building Your First AI Agent



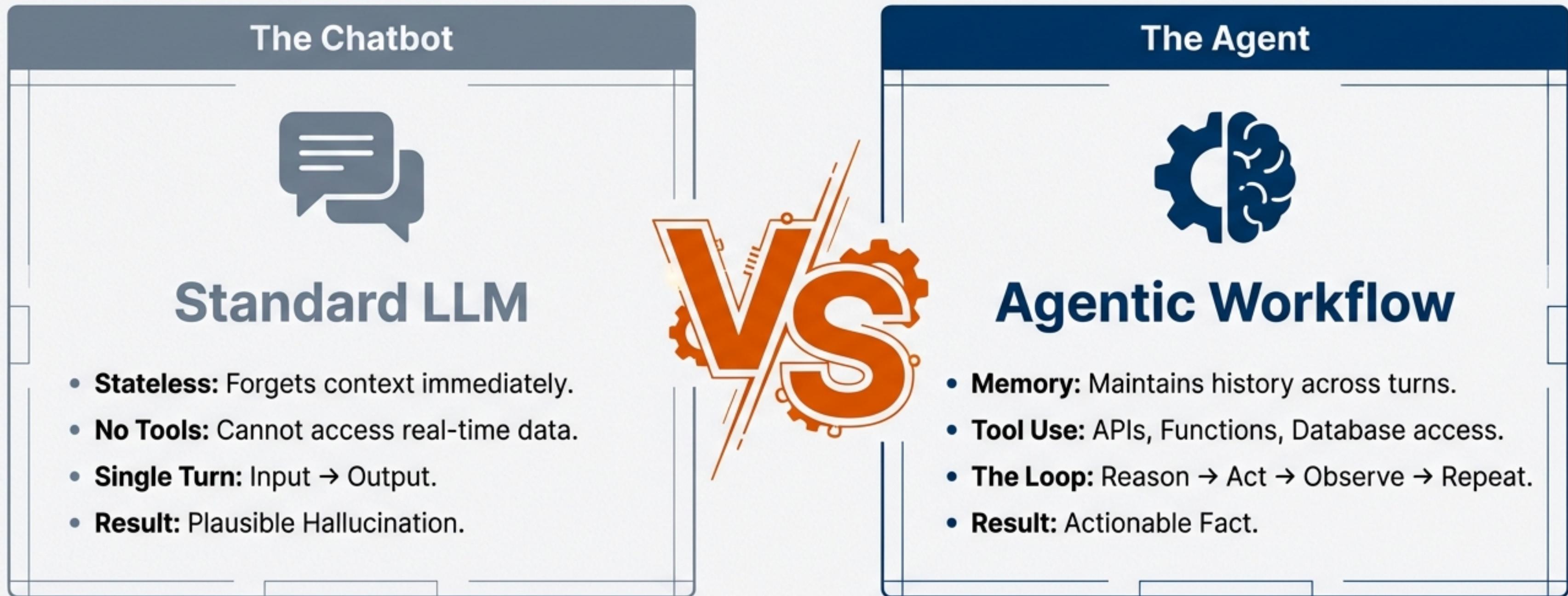
A technical workshop on ReAct patterns,
Tool Calling, and LLM orchestration.

Hypothesis: Do rainy days cause stock prices to drop?

Source: alfasin/stock-weather-agent

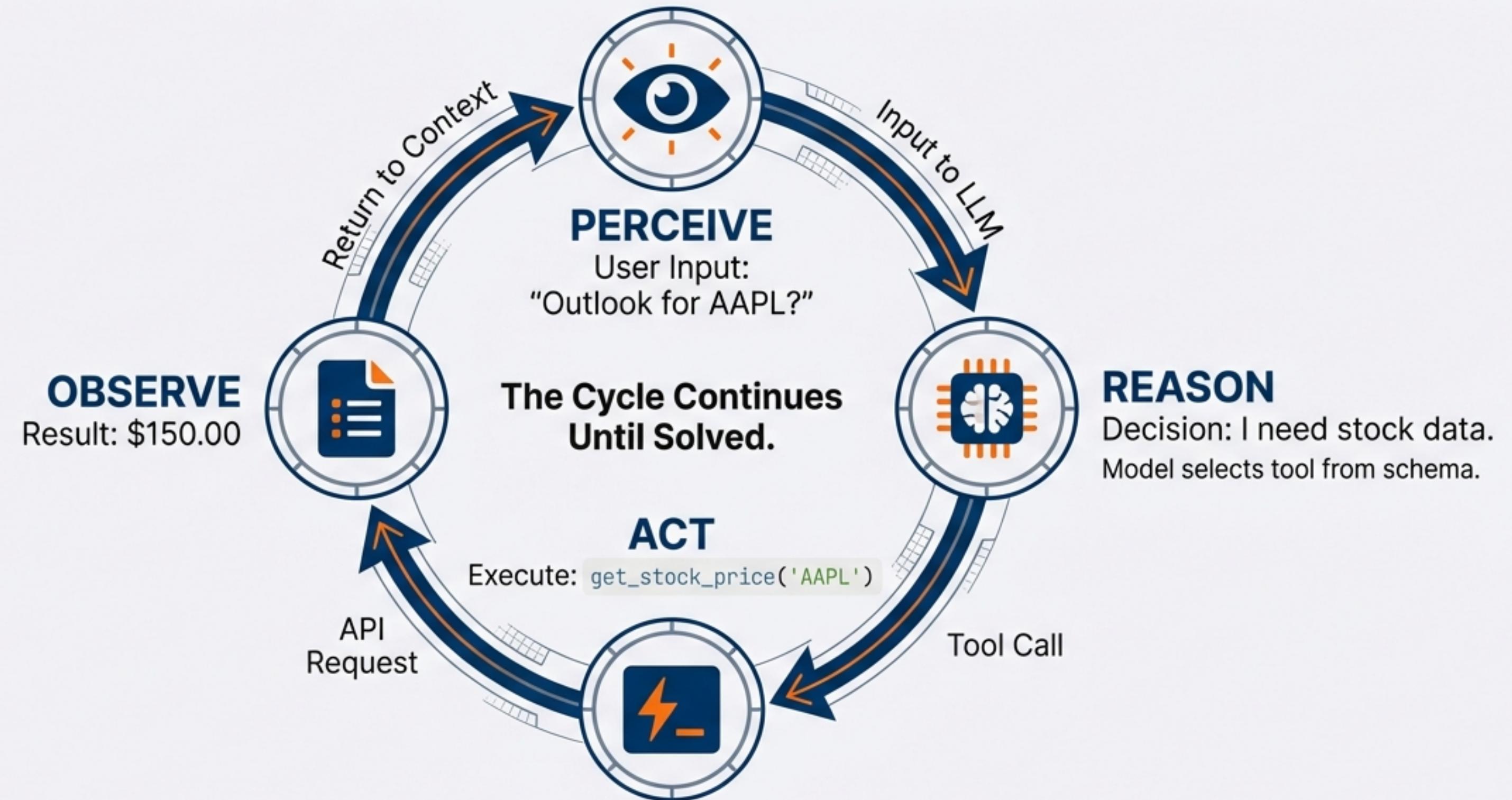
NotebookLM

Chatbots Talk. Agents Do.



To test the Rainy Day Hypothesis, we need to fetch live weather and market data. A chatbot cannot do this. **We need an Agent.**

The Anatomy of Agency: The ReAct Loop



The Engine Room

High-performance stack for local agent development.

The Brain (Inference)



Model: llama-3.1-8b-instant

Speed: Up to 30K TPM (Free Tier)

Role: Fast inference for multi-step loops.

The Data (World Knowledge)



Financial
Modeling
Prep

Real-time Stock Prices



Open-Meteo

Weather WMO Codes (No Key Required)

The Core (Orchestration)



Language: Python 3.10+

Manager: uv (Ultra-fast package sync)

Structure: No frameworks initially. Raw Python.

Initialize the Environment

```
> git clone stock-weather-agent  
> cd stock-weather-agent  
> uv sync  
[uv] Resolved 42 packages in 0.12ms...  
> cp .env.example .env
```

Configuration Guide

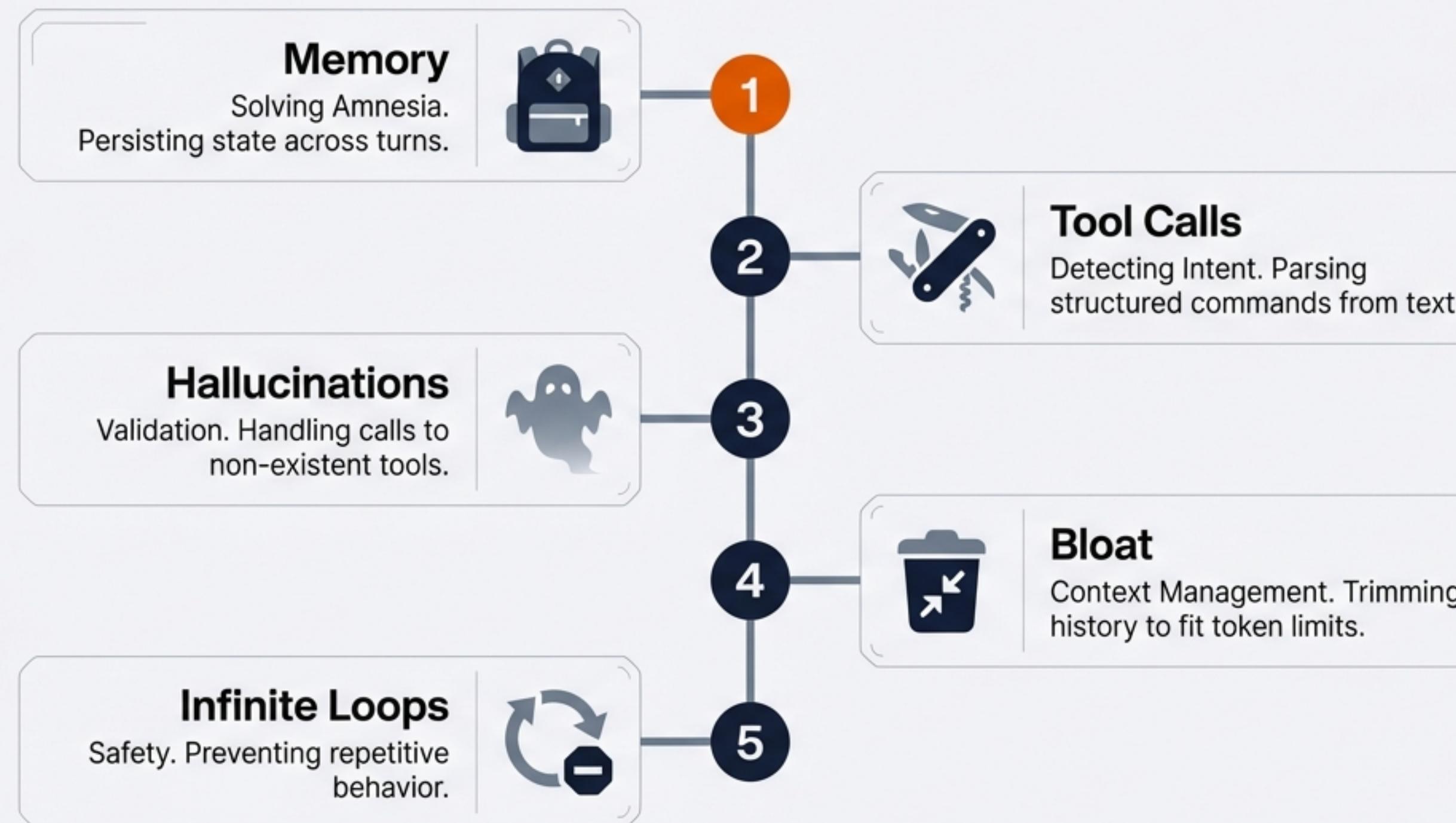
Environment Variables (.env)

1. **GROQ_API_KEY:** [Required]
The reasoning engine.
2. **FMP_API_KEY:** [Optional]
Stocks. Falls back to mock data if missing.
3. **Open-Meteo:** [Free] No key needed.

Run the agent: uv run python main.py "What's the outlook for AAPL?"

Workshop Phase 1: Building the ReAct Agent

Five engineering challenges found in "assignments/react_agent.py"



Engineering Context and Action

Exercise A Inter, Deep Navy (#003366)

The Memory List

```
messages = [
    {"role": "user", "content": "Hi"},
    {"role": "assistant", "content": "Hello!"},
    {"role": "user", "content": "Stock price?"}
]
•
•
•
```

The Context Window.
Must be passed back to the LLM every single time.

Without appending history, the agent is stateless.

Exercise B Inter, Deep Navy (#003366)

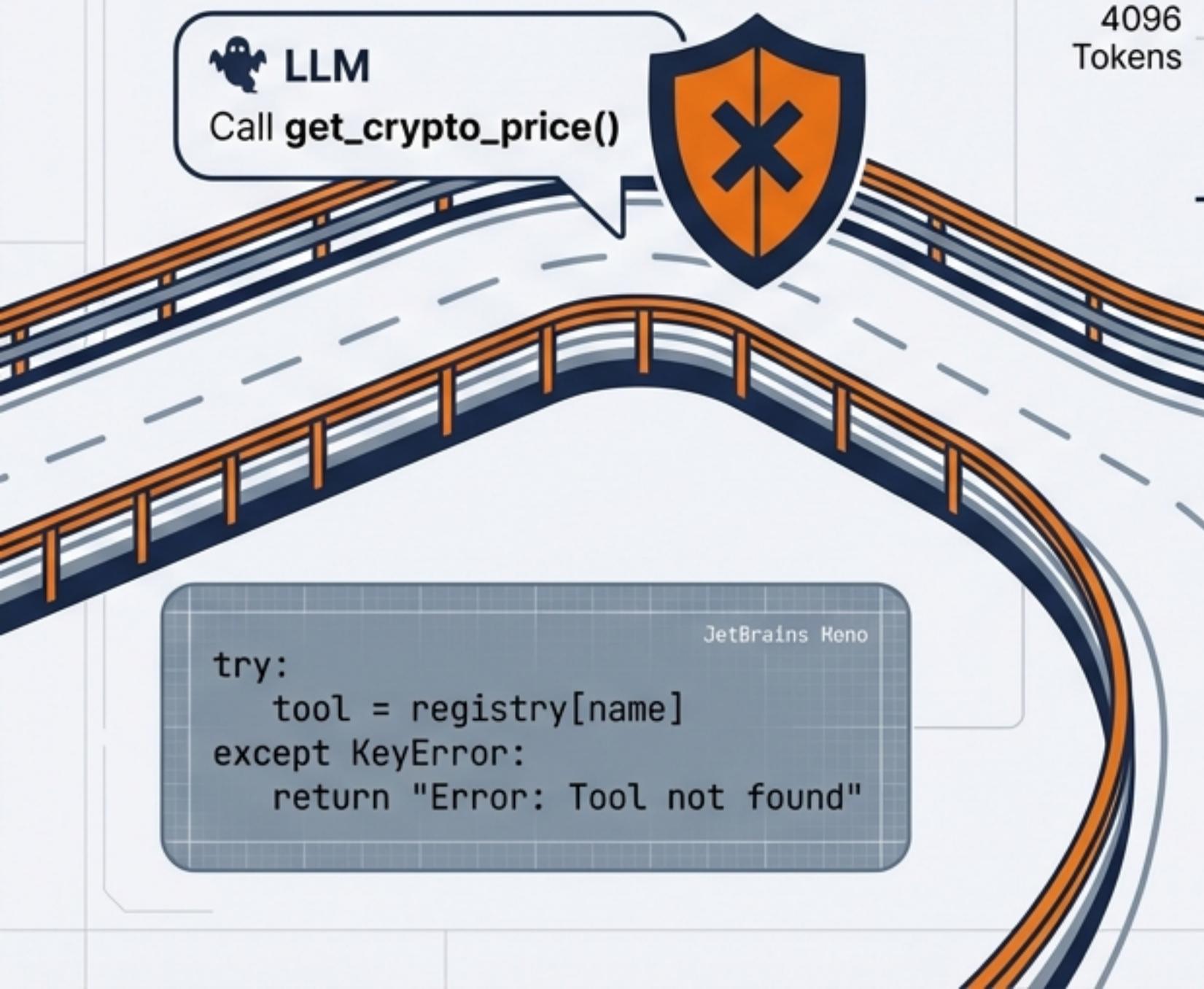
The Decision Tree

```
graph TD
    LLMResponse[LLM Response] --> LLMOutput{LLM Output}
    LLMOutput -- B --> PlainText{Plain Text?}
    PlainText -- YES --> ReturnAnswer[Return Answer to User]
    LLMOutput -- A --> JSONToolCall{Contains JSON Tool Call?}
    JSONToolCall -- YES --> PauseGeneration[Pause Generation. Execute Code.]
```

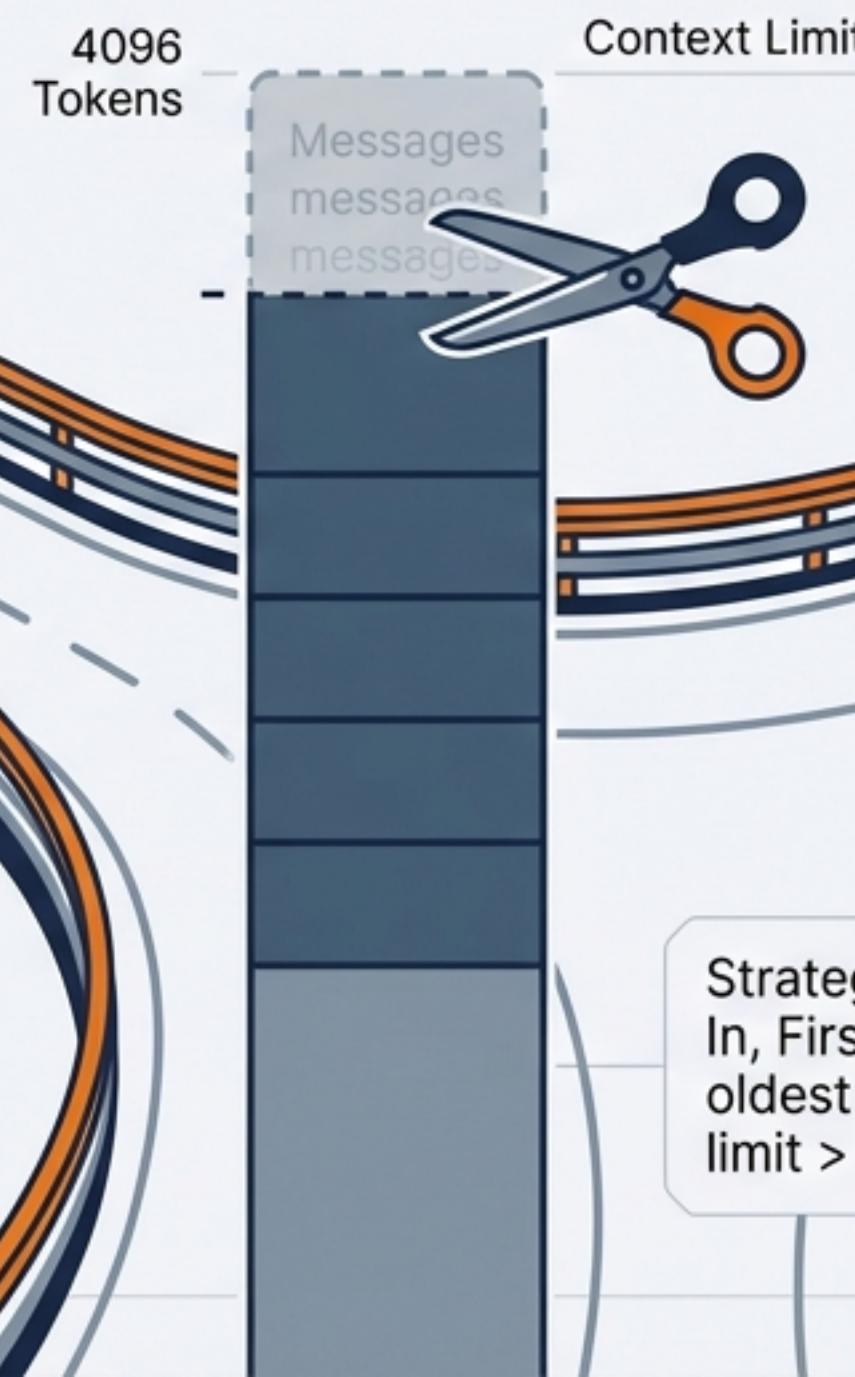
We must programmatically detect if the LLM is 'talking' or 'acting'.

Handling the Chaos (Edge Cases)

Exercise C Hallucinations

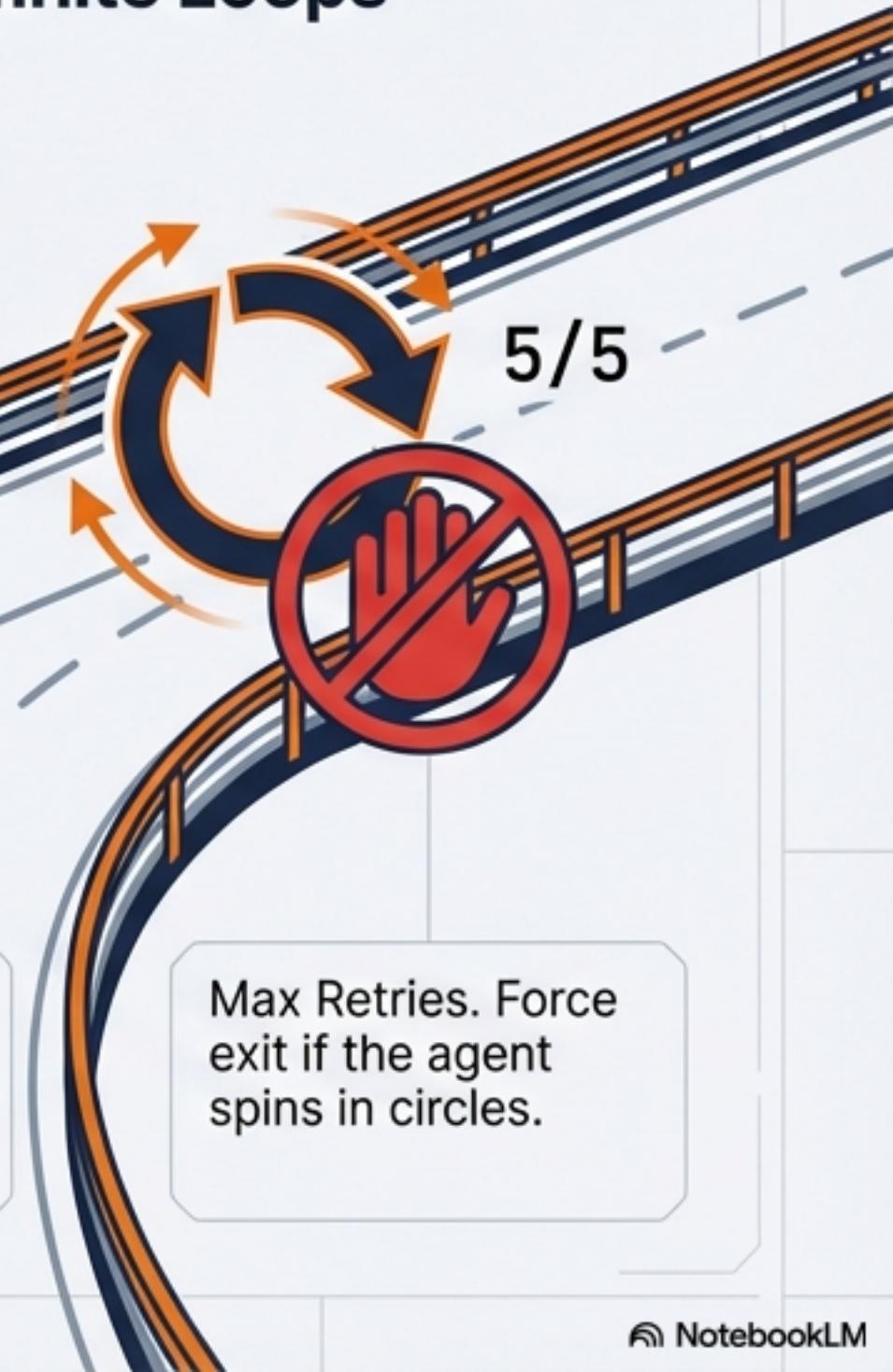


Exercise D Memory Bloat



Strategy: FIFO (First In, First Out). Remove oldest messages when limit > 4096 tokens.

Exercise E Infinite Loops



The 'Hello World' of Tooling

Stock Tool

tools/stock_tool.py

```
JetBrains Mono
def get_stock_price(ticker: str):
    """Get current price and daily change."""
    # Check cache (24h validity)
    if ticker in cache: return cache[ticker]

    # Call FMP API
    return requests.get(f".../quote/{ticker}")
```

Includes **caching** to save API limits.

Weather Tool

tools/weather_tool.py

```
JetBrains Mono
def get_weather(city: str):
    """Get weather & interpret WMO codes."""
    data = open_meteo.get(city)
    code = data['current']['weather_code']

    # 51-67, 80-82 indicate rain
    is_raining = code in [51, 53, 55, 61, ...]
    return {"rain": is_raining, "temp": ...}
```

Logic layer converts raw codes to semantic meaning (Rain/No Rain).

Workshop Phase 2: The Planning Agent

Alternative Pattern: Plan first, then execute.

Step 1: The Plan

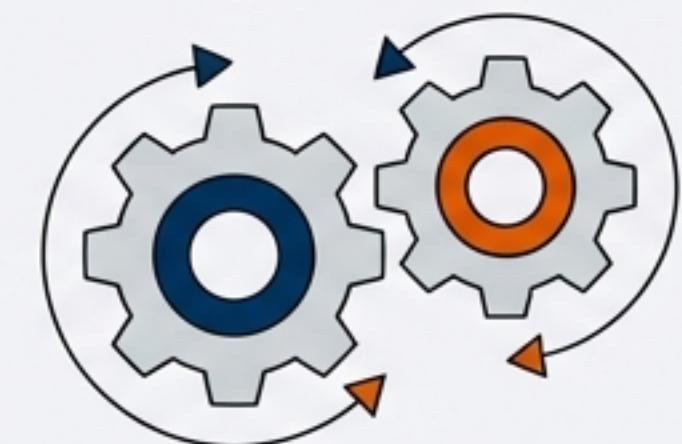


Generate Plan

```
["get_weather", "get_stock"]
```

LLM reviews request and lists all necessary tools upfront.

Step 2: Execution



Parallel Execution

System fires all tool calls in the list. No waiting for intermediate reasoning.

Step 3: Synthesis



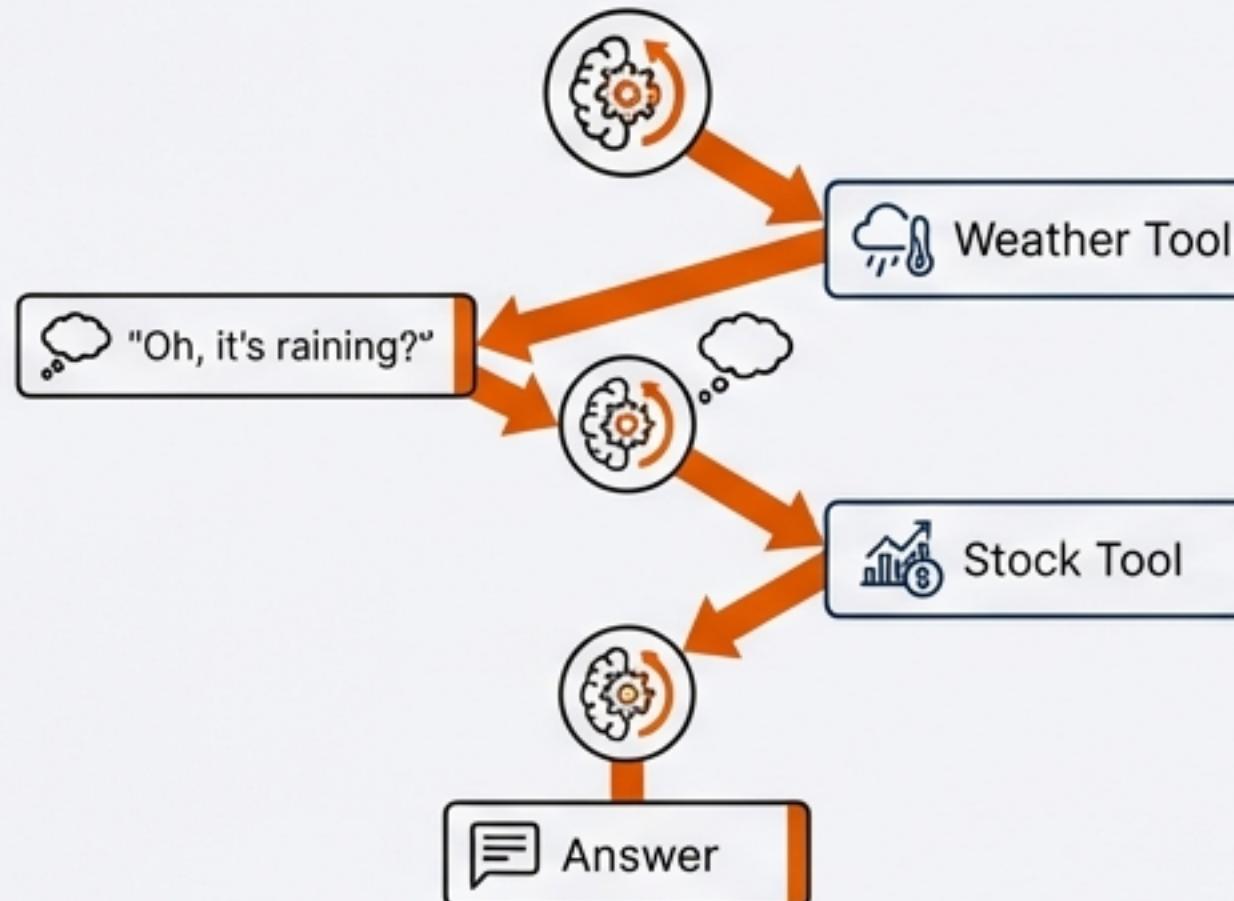
Final Response

LLM receives all data at once and writes the answer.

Pattern Comparison

Query: "What's the outlook for NVDA in NYC?"

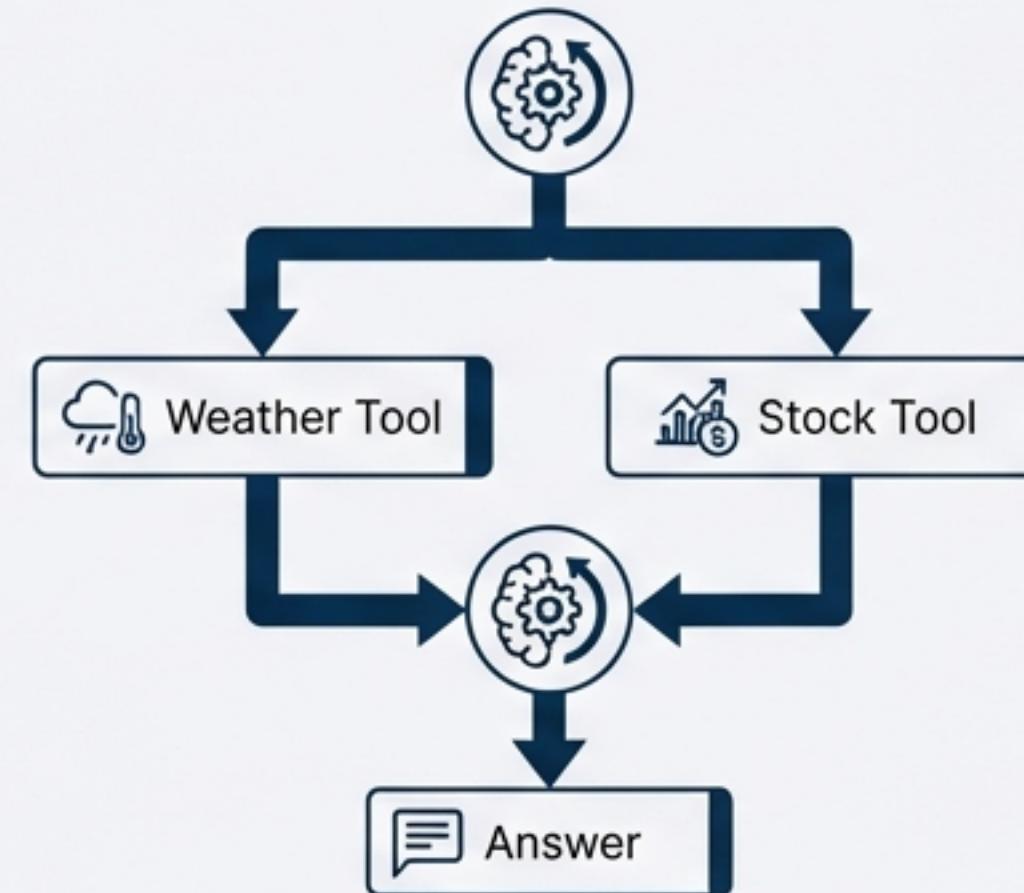
ReAct (The Zig-Zag)



Interleaved Reasoning

Best For: Dynamic tasks where step 2 depends on step 1.

Planning (The Fork)



Sequential/Parallel Execution

Best For: Tasks with known, independent steps.

Run the planning agent: `uv run python main.py --planning ...`

The Result: Testing the Hypothesis

User: I'm looking at MSFT stock. Check the weather in New York and tell me what you think.

[Agent] Thinking...

[Tool] Calling get_weather('New York')

[Obs] Rain detected (Code 61).

[Agent] Thinking...

[Tool] Calling get_stock_price('MSFT')

[Obs] Price: \$410.00 | Change: -0.5%

[Agent] Response:

"Given it is currently raining in New York, the 'Rainy Day Hypothesis' suggests a bearish outlook. MSFT is trading at \$410.00, down 0.5% today. The hypothesis holds true for now."



The Abstraction Layer

Manual Implementation vs. Framework ('pydantic-ai')

The Hard Way (Manual)

```
def get_weather(ctx, city: str):
    # Manual implementation details omitted for brevity.
```

150 lines of loop logic, JSON parsing, error handling, and history management.

```
    # Manual implementation details omitted for brevity.
```

The Smart Way (Framework)

```
```  
@agent.tool
def get_weather(ctx, city: str):
 return "It is raining in NYC."
 20 lines. The framework
The entire ReAct loop in one line!
result = agent.run_sync("How is NVDA doing?")
```
```

Building from scratch teaches you **how** it works. Frameworks let you scale it.

Start Building

GitHub Repository



github.com/alfasin/stock-weather-agent

Next Steps

1. **Fork** the repository.
2. **Complete** the TODO items in `assignments/react_agent.py`.
3. **Compare** your manual loop against `bonus/pydantic_ai_version.py`.

“

You have the tools. Now go prove—or disprove—the hypothesis.”

