Vizuara AI Agents Bootcamp Day 5

Smolagents: The simplest AI Agent coding library

VIZUARA AI
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In this post, we'll break down the key takeaways from **Day 5 of the Vizuara AI Age Bootcamp**. **Day 5** was all about **SmolAgents**, a new framework called *"the simplest agents library."*

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(1) SmolAgents at a Glance: Many Agents, One Framework

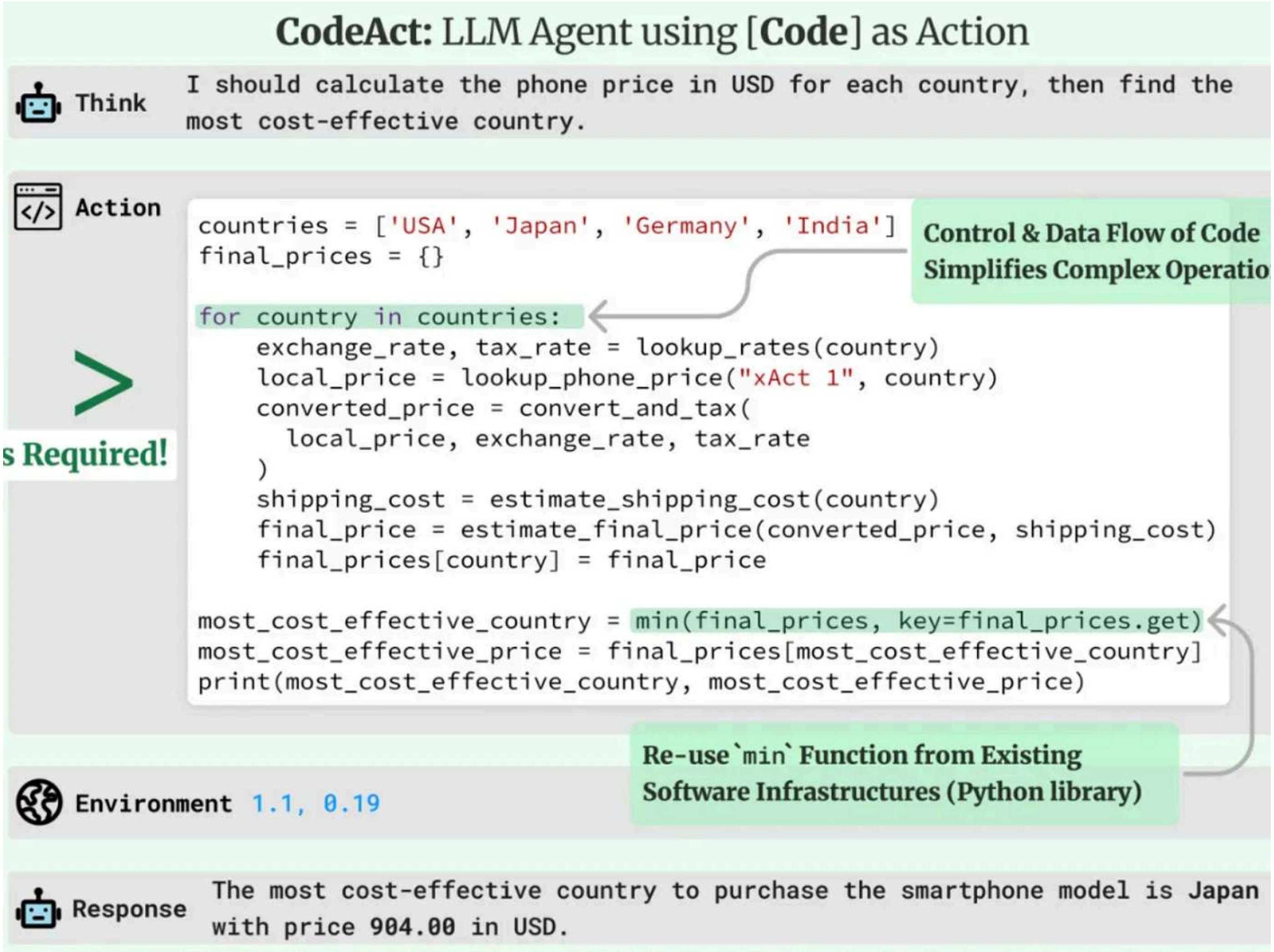
SmolAgents keeps things simple but versatile. It provides a range of agent types an capabilities under one roof:

- **Vision + Browser Agents:** Agents that can interpret visual data (images/screenshots) and even navigate the web. *Imagine an agent that "sees" a webpage or an image and interacts with it like a human would!* This opens up possibilities for UI automation and image understanding.
- **Code Agents:** Agents that **write Python code** as actions to use tools and solve tasks. These agents leverage a language model to produce code (for example, calling a function) which the framework executes. Code Agents are powerful because they can implement complex logic and multi-step operations within a single thought.
- **Tool-Calling Agents:** Agents that invoke tools through structured **JSON-like c** or text instructions. This is the more classical approach where the AI outputs a action in a predefined format (like a JSON specifying which tool to use and wit what input). It's more constrained than code execution, but easier to predict an parse.
- **Multi-Agents:** Support for orchestrating **multiple agents** together. One agent c manage or call other agents as tools (hierarchical agents). This enables complex

workflows where specialized sub-agents handle parts of a task, coordinated by manager agent.

- **Retrieval Agents:** Agents augmented with **retrieval abilities** – for example, pul in information from a knowledge base or the web to ground their answers. Thi: essentially *RAG (Retrieval-Augmented Generation)* in agent form: the agent has a tool to search documents or vector databases and uses those results in its reasoning.
- **Built-in Tools:** A collection of handy **tools** that come with SmolAgents to get y started. These include things like web search, a Python code interpreter, and ev a speech-to-text transcriber. Tools are basically functions an agent can call – ar you can easily add custom ones. By having a good set of tools, SmolAgents ensu your agents can take actions in the world (like fetching web content or doing calculations).

(2) Code vs JSON: SmolAgent's Code-First Philosophy



A standout feature of SmolAgents is that it lets the AI agent **call tools by writing co not just by filling out a JSON schema**. Traditional agent frameworks often have th model output a structured plan or JSON indicating something like: `{"action": "Search", "input": "Python tutorials"}`. SmolAgents takes a different route asks the model to produce a snippet of Python code that directly calls the tool functions needed.

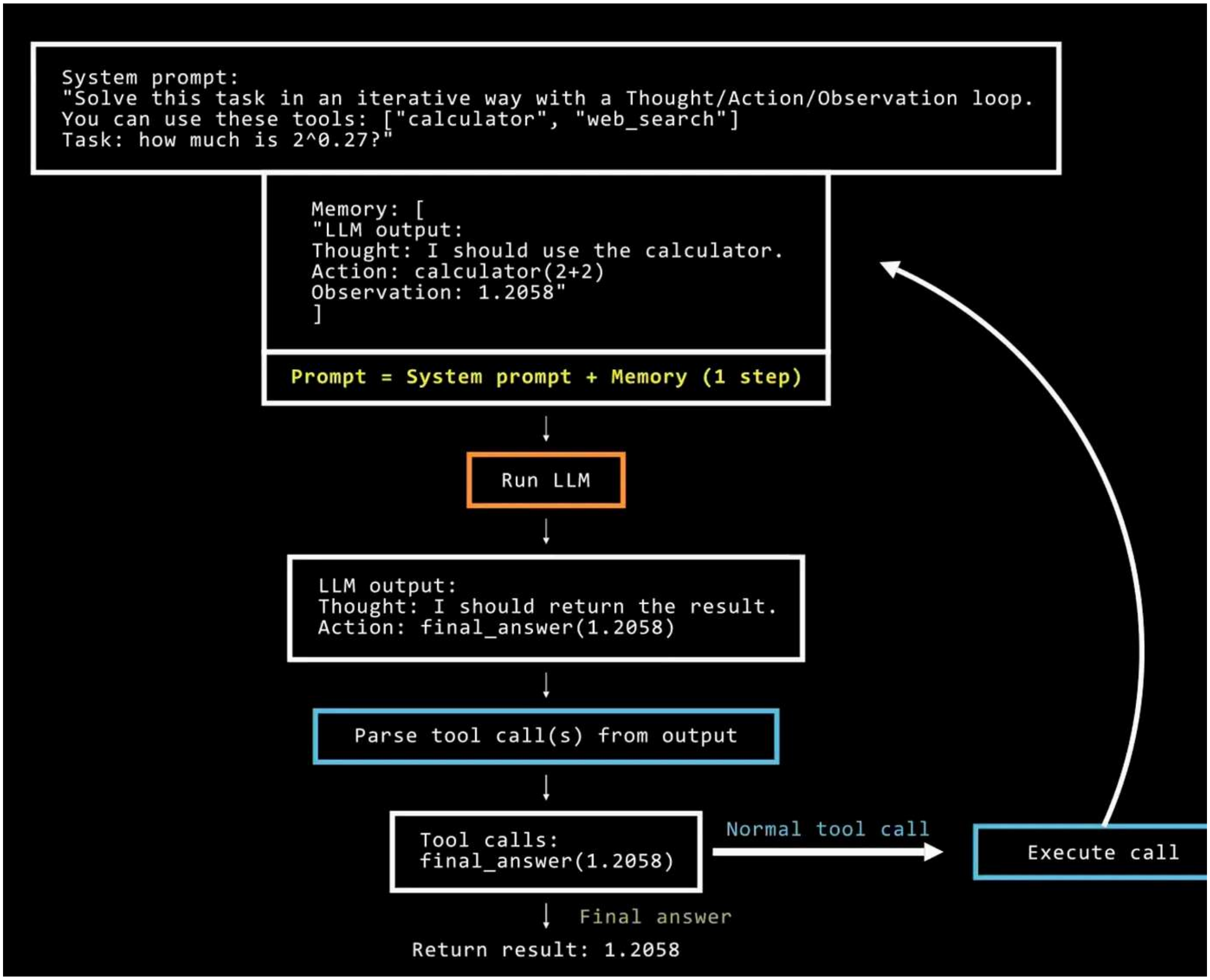
Why code? Writing actions as code has some big advantages:

- **More Flexibility:** The agent can use the full flexibility of Python for logic. It ca loop, branch, or combine multiple tool calls in one go. For example, the agent could write a loop to perform several web searches and filter results – tasks tha would be clunky as separate JSON calls.

- **Fewer Steps:** Because the agent can do more in one action, it often needs fewer iteration cycles to solve a problem. In fact, early benchmarks showed that code based agents can use ~30% fewer reasoning steps (and thus fewer LLM calls) wh achieving better results.
- **Human-Like Thought Process:** When the AI writes code, it's almost like seein its thought process in an executable form. It can be easier to trace what the age is trying to do by reading the code, which can aid debugging or understanding agent's reasoning.
- **JSON Option Remains:** Of course, SmolAgents still supports the classic JSON- style tool calls via the **ToolCallingAgent**, which you might use for simpler or m constrained tasks. But the default and the star of the show is the **CodeAgent**.

The code-first approach does introduce new considerations: executing arbitrary co means you have to think about safety (SmolAgents includes options like secure interpreters or sandboxes for running code safely). But for many cases, the trade-of worth it because of the boost in capability and efficiency. Next, let's peek into *how* a CodeAgent actually operates step by step.

(3) Inside the CodeAgent Loop: How Does It Work?



So, what happens under the hood when you run a SmolAgents CodeAgent? It's an iterative loop that follows the **ReAct paradigm** (Reason + Act) with a twist that acti are code. Here's the typical flow in a CodeAgent's cycle:

1. **Task Input & Setup:** You give the agent a task or question. This is added to the agent's memory (which stores the conversation and results so far). A system prompt is initialized, describing the agent's role and available tools.
2. **Thought/Action Generation:** The agent (via the LLM) generates the next actio take, formatted as a Python code snippet. For example, it might produce code calling a `web_search("keyword")` or doing a calculation. This is essentially th "thought" turned into an executable action.

3. **Tool Execution:** The generated code is then executed by the agent. If the code calls a tool (like a search), that tool runs and returns output. The code could als contain simple logic (e.g., loops, if-statements) combining tool results.
4. **Observation & Memory Update:** The result of the tool call (the observation) is captured. The agent logs this outcome and appends it to its memory (so the transcript of what's happened so far is stored). The memory now includes: the initial question, the action taken, and the observation obtained.
5. **Repeat Loop:** With the updated context, the agent goes back to step 2. The LLI gets to see the conversation history including the latest result, and decides on t *next* action (again, as code). This loop of thought → code action → execution → observation continues, allowing the agent to make multi-step reasoning progre
6. **Final Answer:** Eventually, the agent determines it has enough information or h completed the task. At that point, instead of calling a regular tool, it calls a spe tool named `final_answer(answer_text)`. This is a signal that the agent is do The argument to `final_answer` is the answer it wants to give. When the framework sees `final_answer` called, it ends the loop and returns that answer you.

Throughout this process, the **agent's memory** ensures continuity – it "remembers" previous actions and their outcomes. This prevents it from repeating work or contradicting itself. If the agent hits an error (say the code had a bug or a tool failec that error message can also be logged to memory so the AI can reconsider in the ne step.

The result is an agent that incrementally reasons and gathers info, much like a pers would solve a problem step-by-step. It's quite fascinating to watch a CodeAgent in action, because you see it writing and executing code in real-time to figure things o

(4) ToolCallingAgent vs CodeAgent: A Quick Comparison

Both ToolCallingAgents and CodeAgents can accomplish complex tasks, but they h different strengths. Here's a side-by-side comparison of these two agent styles with SmolAgents:

Feature	ToolCallingAgent	CodeAgent
Complexity	Lower complexity	Higher complexity
Flexibility	Structured and predictable	Highly flexible and dynami
Arbitrary code	No	Yes
Typical tasks	Simple, structured tasks	Complex, unstructured tas
Error risk	Lower (predictable execution)	Higher (can have runtime errors)
Security implications	Safer (API calls only)	Needs caution (executes Python)

Both agents use the same underlying logic (they both are multi-step ReAct agents), in fact SmolAgents lets you choose whichever style suits your use case.

If you want quick and safe prototyping, a ToolCallingAgent might suffice. If you ne
the agent to truly *think in code* and handle complex sequences in one shot, the CodeAgent is your friend.

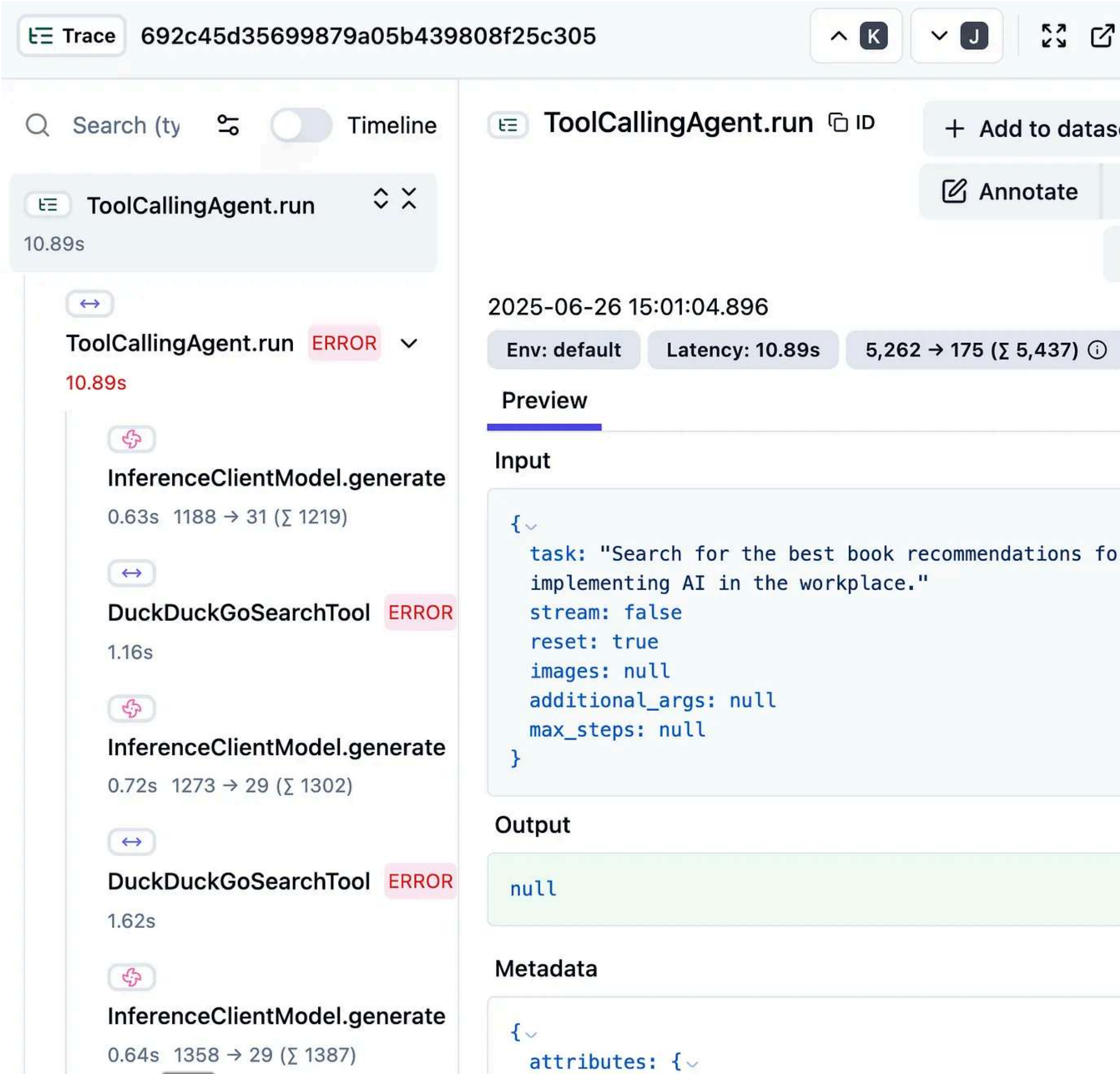
Often, the extra power of code comes with the responsibility to handle it safely – bu
SmolAgents provides tools to help, like secure execution modes.

(5) Vision Agents

Finally, we hinted at **Vision Agents** in the session – agents that can see. This mean
the agent can accept image inputs or use a visual perception tool as part of its toolb
For instance, a vision-enabled agent could analyze a chart image you give it, or con
a web browser by interpreting screenshots of a page (just like a human scanning a webpage).

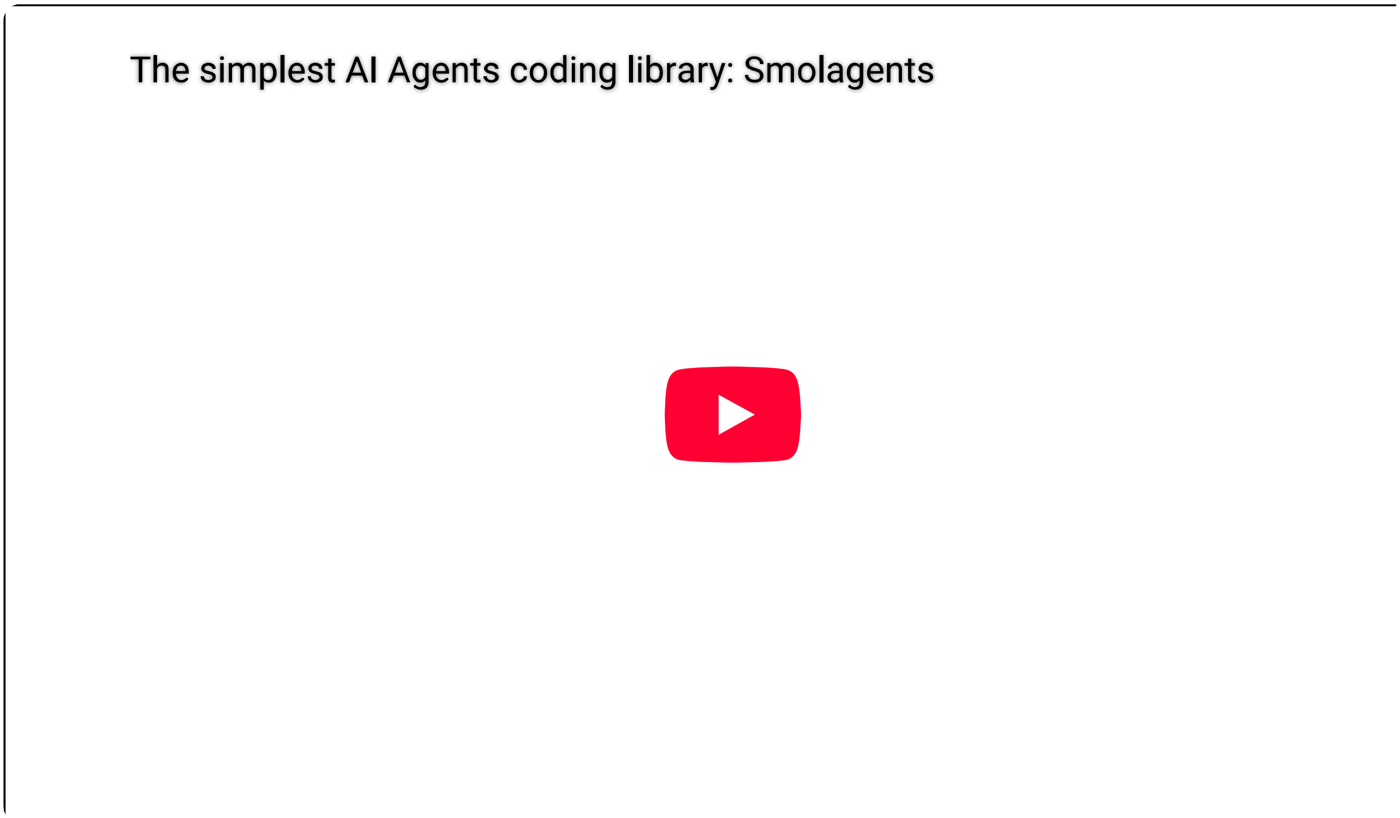
SmolAgents supports vision models, which allows agents to tackle tasks that involv
images or a visual environment.

(6) LangFuse



We wrapped up Day 5 by exploring **Langfuse**, a powerful observability platform tailored for LLM agents. Using Langfuse, participants learned to track, visualize, ar debug agent outputs effortlessly. By logging agent actions, tool calls, and reasoning steps, Langfuse provided deep insights into the behavior of our SmolAgents—helpi us understand performance bottlenecks, logic flow, and areas for improvement. It's invaluable companion when building robust, transparent AI agents.

(7) Wrapping up Day 5



That's a wrap for Day 5.

SmolAgents shows that sometimes less is more – with a lean setup and letting the do the heavy lifting by writing code, we can build very capable agents. We covered core idea of code vs JSON tool use, walked through how an agent reasons in loops, compared the two agent styles.

Feel free to experiment with SmolAgents on your own – it's open-source and quite "smol" (the core is under 1,000 lines of code!)

See you in the next lecture!

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pls provide colab link for running code

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