LLM Agents

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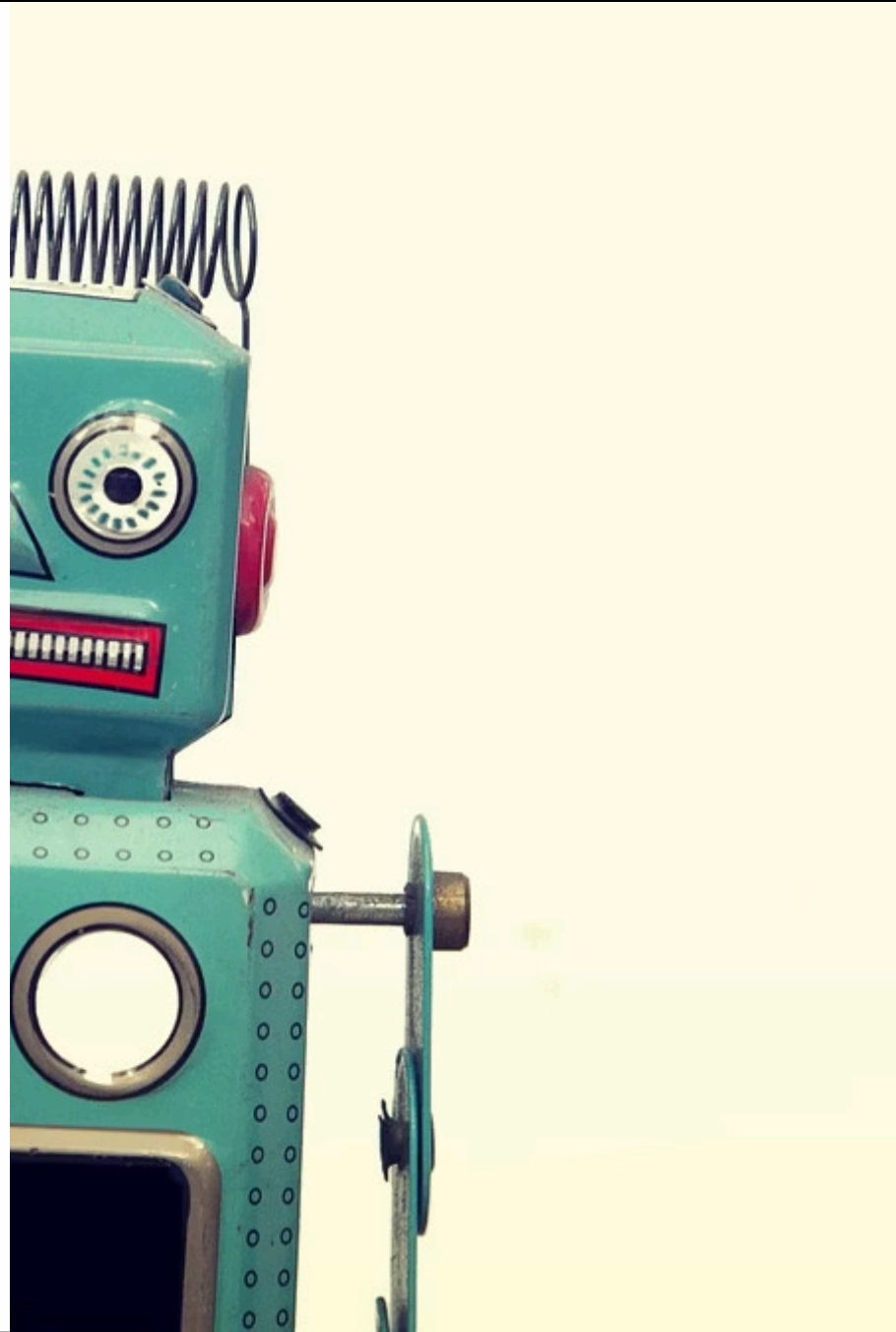

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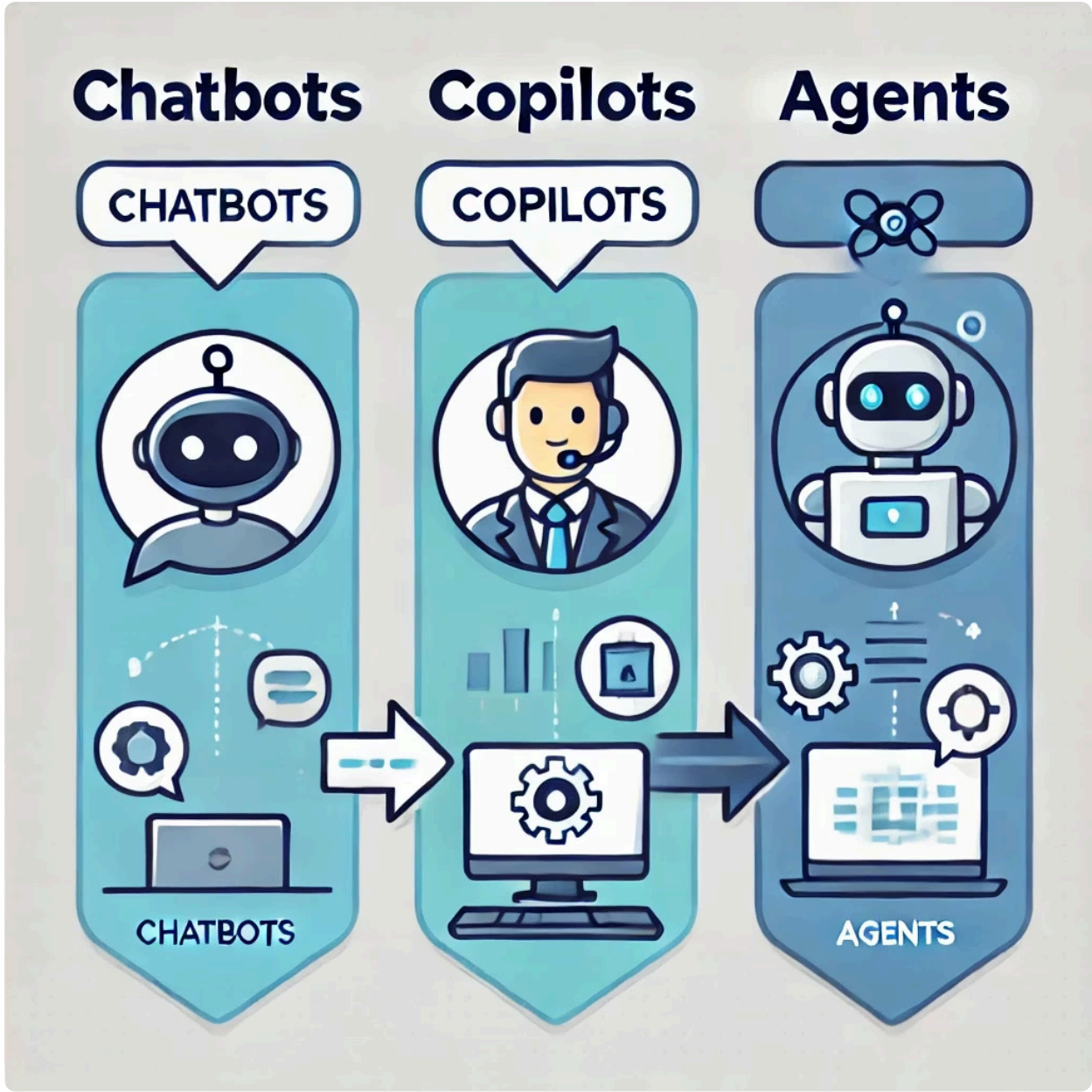
AI-based Chatbots

Assistants, co-pilots and agents that enable natural conversation and execution of complex tasks.


Chatbots
Copilots
Agents
CHATBOTS
COPILOTS
CHATBOTS
AGENTS

Chatbots

Definition

Software designed to imitate human conversations, mainly through text. Its motivation is to assist the user with a specific task.

Pre-LLM Chatbots

They are based on predefined responses and have limited capacity to handle complex or ambiguous queries.

LLM-based Chatbots

With generative AI, chatbots can better understand user questions and provide more accurate and natural responses.

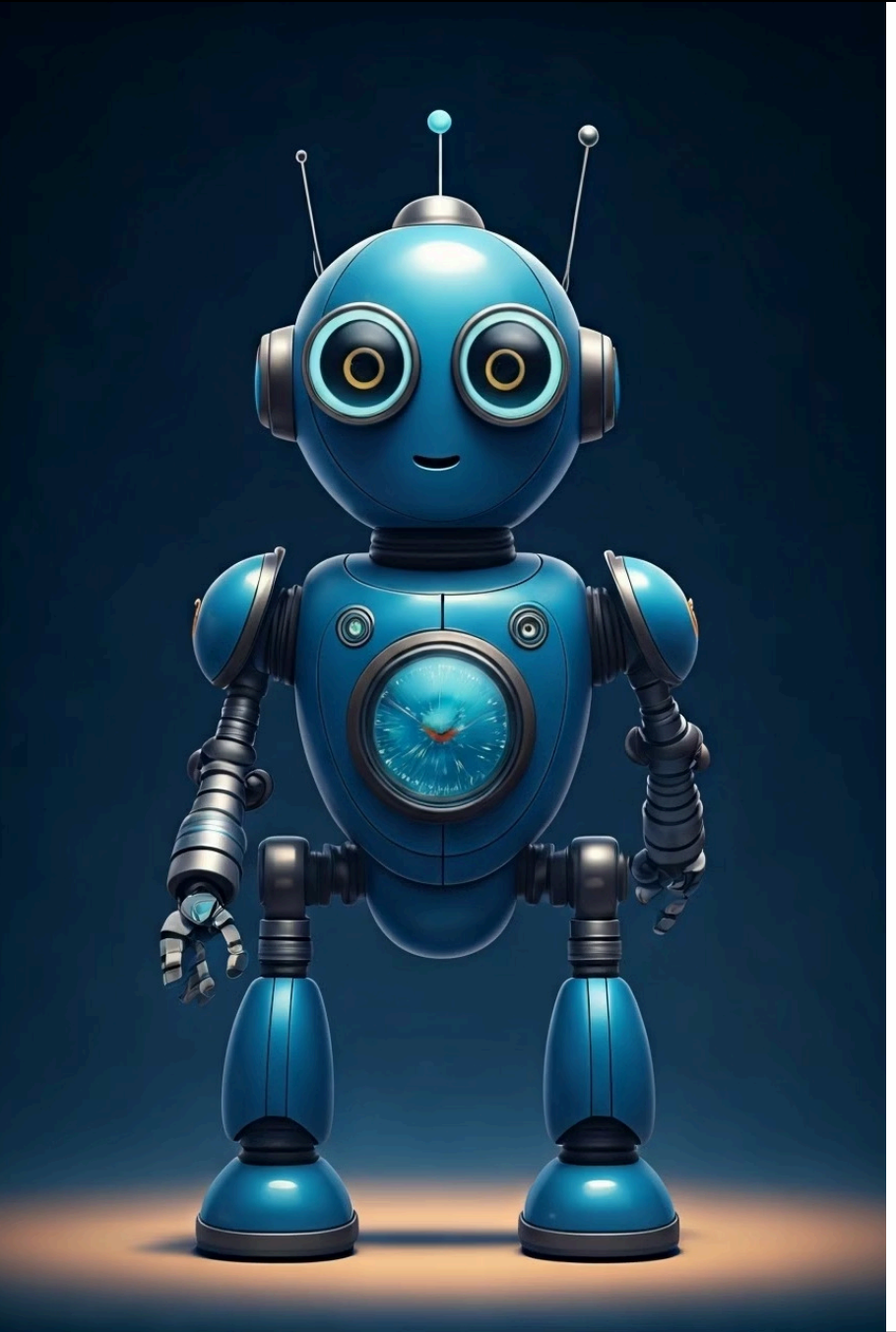
Co-pilots

Features

- Real-time collaboration with the user
- Personalised recommendations based on context
- Continuous evolution through machine learning
- Seamless integration with the tools used daily

Benefits

- Optimisation of time and resources
- Minimisation of mistakes and errors
- Accelerated and effective learning



Agents

Autonomy

Capable of making independent decisions based on objectives and context.

Multifunctionality

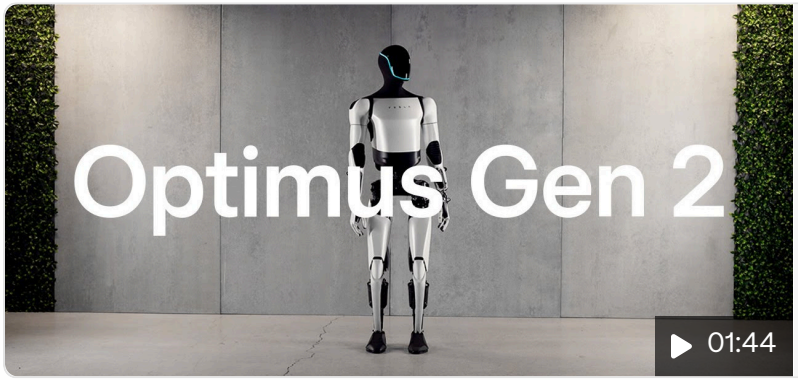
Integrate various tools and APIs to perform complex tasks.

Collaboration

Interact with other agents and systems to solve problems in a coordinated manner.

Adaptability

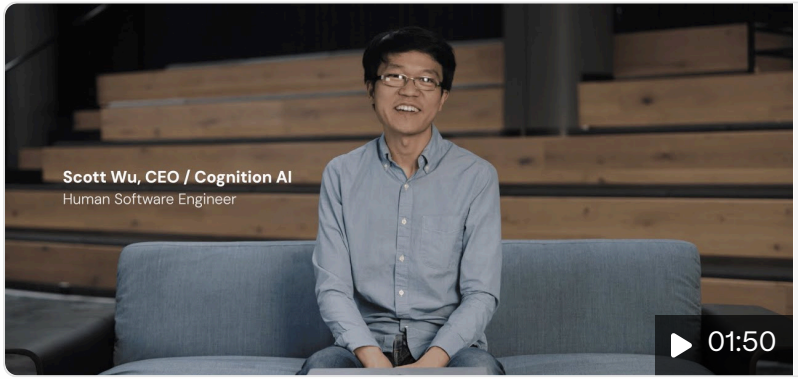
Adjust to changes in the environment and improve over time.



YouTube

Optimus – Gen 2 | Tesla

New bot in town! Optimus Gen 2 features Tesla-designed actuators and sensors, faster and more capable hands, faster walking, lower total weight, articulated...



YouTube

Introducing Devin, the first AI software engineer

Meet Devin, the world's first fully autonomous AI software engineer. Devin is a tireless, skilled teammate, equally ready to build alongside you or independently...

Characteristics of LLM Agents

Streaming Conversation

Fluid real-time responses, enhancing interaction.

Context Information

Access to internal and external data, via KAG, for more complete responses.

Contextual Memory

Remembers previous conversations for more accurate responses.

Tool Integration

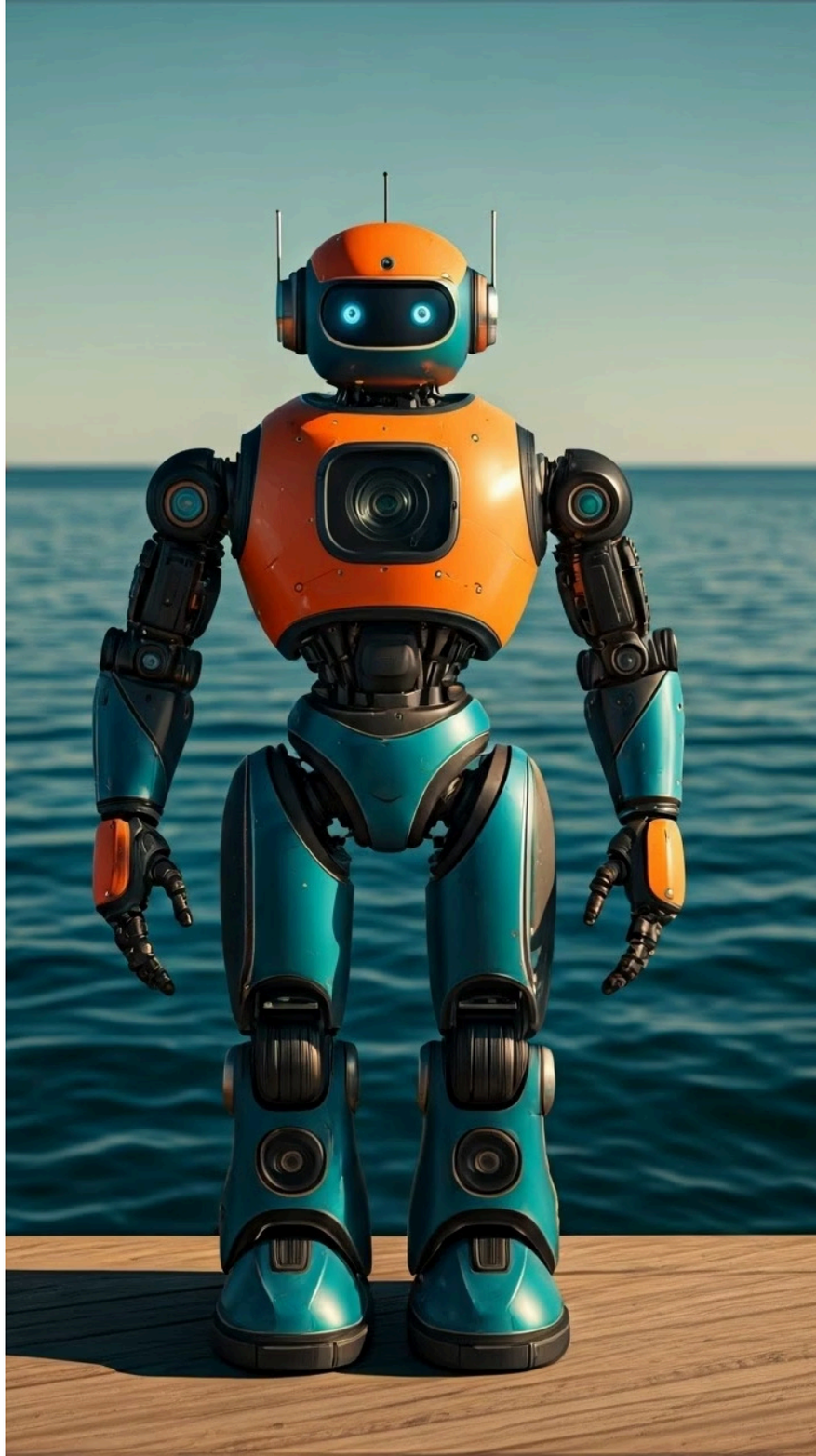
Uses APIs and external services to expand its capabilities.

Collaboration between Agents

Teamwork with other agents to solve complex problems.

Adaptability

Adapts to changes and takes initiative.



RAG modular

Limitations of Naive/Advanced RAG

Complex Thinking

Complex problems often require multi-step reasoning. A single information retrieval step may not be enough.

Human Processes

Humans, when writing, make mistakes, backtrack and correct to achieve quality. LLMs also suffer this limitation.

The (human) process of writing a text

1

Plan an outline

Define the structure of the text to ensure coherence and clarity.

2

Research

Search for relevant information on the Internet to complement and enrich the content.

3

First draft

Write a first draft to organise the ideas and main content.

4

Review the draft

Identify weak arguments and remove superfluous information.

5

Rewrite

Rewrite the draft to correct the weaknesses identified.

6

Iterate

Repeat the previous steps to improve the quality of the text.

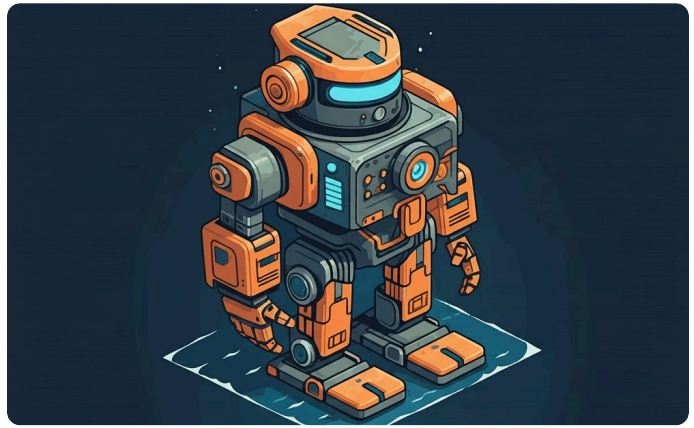
RAG modular

Modularity

This technique allows adding or replacing RAG components according to the specific needs of the task.

Adaptability

The modularity of RAG allows adapting the system to various tasks and contexts, offering greater flexibility and control.



RAG Patterns

In addition to the *Naive* and *Advanced* patterns, other patterns have emerged that allow increasing and refining the context in order to handle more complex tasks.

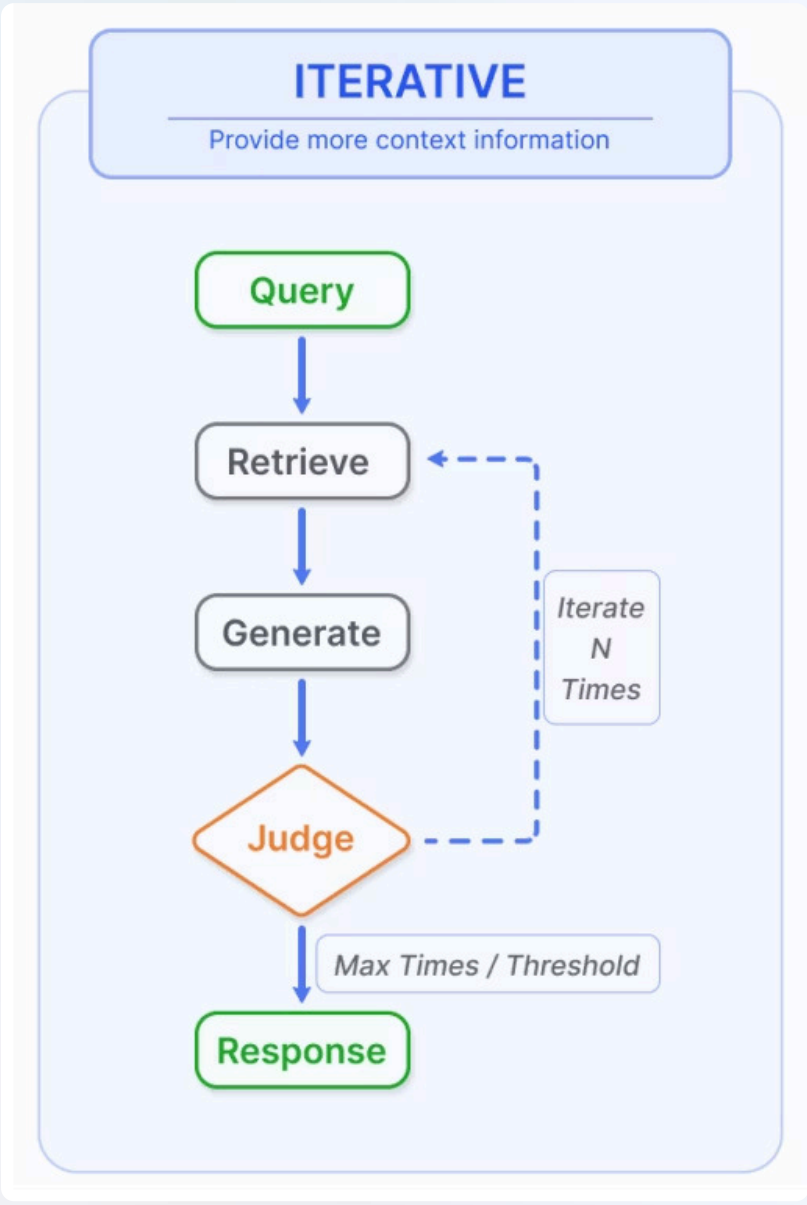
Multi-step augmentation: iterative

Query: "I would like information about the master's programmes offered at the ESI"
Retrieve: The system searches for and retrieves a list of available master's programmes.
Generate: "Master's in Cybersecurity, Master's Research in Engineering."
Judge: The response is incomplete, as details such as duration and admission requirements are missing.

Query: "What is the duration and admission requirements for the Master's in Cybersecurity?"
Retrieve: The system searches for and retrieves information about this master's programme.
Generate: "The Master's in Cybersecurity consists of 60 credits and requires a Degree in Computer Engineering"
Judge: The response is incomplete, as I still lack information about the Master's Research in Engineering.

Query: "What is the duration and admission requirements for the Master's Research in Engineering?"
Retrieve: The system searches for and retrieves information about this master's programme.
Generate: The Master's Research in Engineering consists of 60 credits and requires any Engineering Degree.
Judge: The response is now complete.

Response: "I will now provide you with the available master's programmes and the information I have about them..."



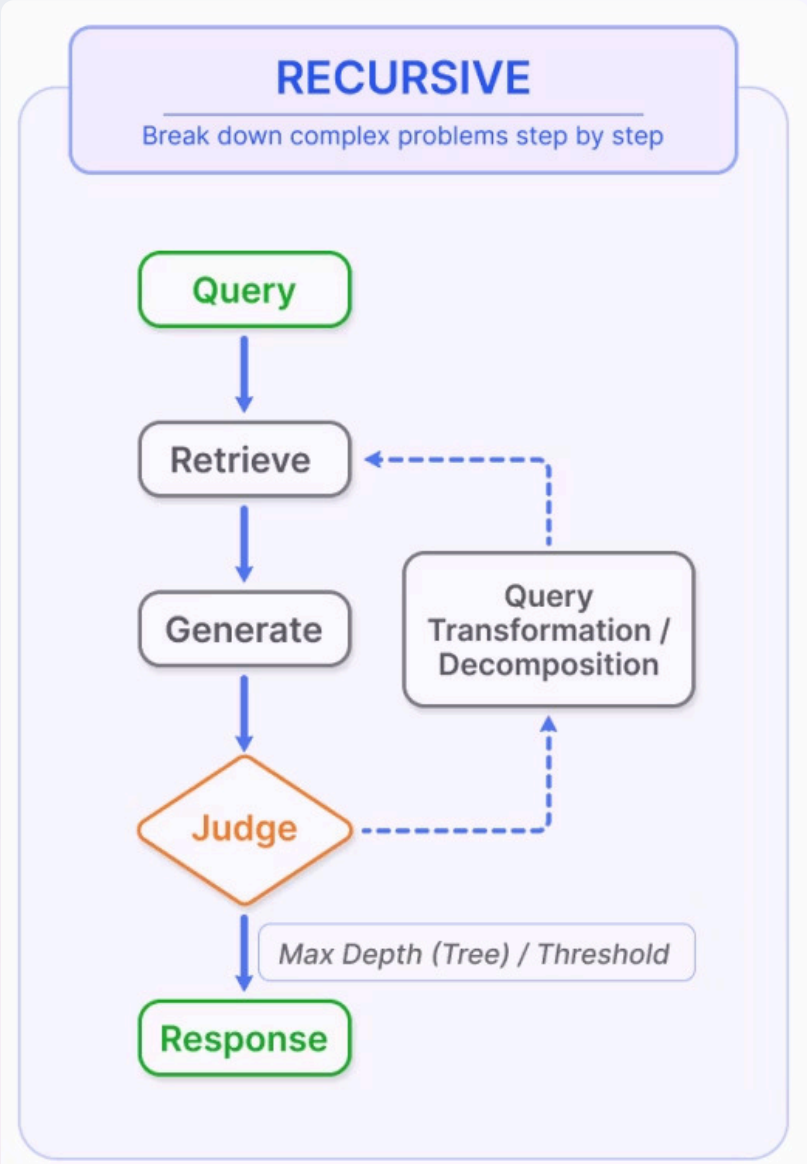
Multi-step augmentation: recursive

Query: "What research projects is the University of Cádiz (UCA) carrying out in the area of renewable energy?"
Retrieve: The system searches for and retrieves general information indicating that the UCA has a research project on offshore wind energy.
Generate: "The University of Cádiz is carrying out a research project on offshore wind energy."
Judge: The response is incomplete, as it lacks detailed information about this specific project.

Query: "What is the main objective of the University of Cádiz's offshore wind energy project?"
Retrieve: The system searches and finds the main objective of the project.
Generate: "The offshore wind energy project aims to study the feasibility of installing wind farms on the coast of Cádiz."
Judge: It is detected that more detail is still needed on the project's results.

Query: "What are the results obtained so far in the offshore wind energy project?"
Retrieve: The system finds the preliminary results of the project.
Generate: "The preliminary results show a high potential for the installation of wind farms in certain areas of the Cádiz coast."
Judge: The response is now complete and provides detailed information about the project.

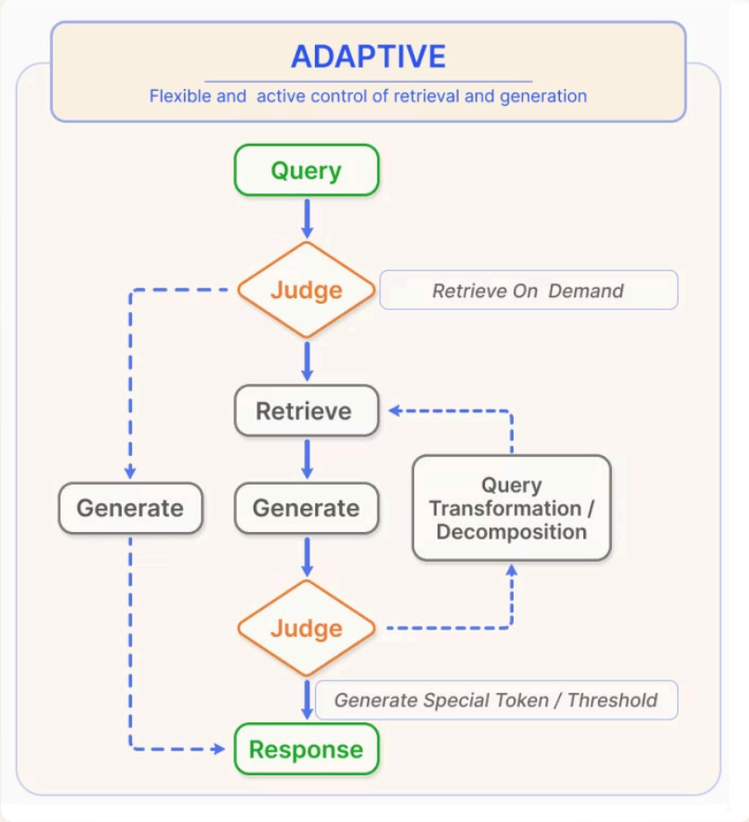
Response: "The University of Cádiz is carrying out a research project on offshore wind energy. The objective is... The preliminary results indicate..."



Multi-step augmentation: adaptive

Query: "What research projects is the UCA carrying out in the area of renewable energy?"
Retrieve: The system searches for and retrieves general information indicating that the UCA has a research project on offshore wind energy.
Generate: "The University of Cádiz is carrying out a research project on offshore wind energy."
Judge: The model wonders if it is necessary to obtain more details to adequately answer the original question. Given that the original question is general, it decides that it has enough information and does not perform any further searches. However, recognising that the user may want more details about these projects, the system prepares to offer additional information if the user requests it.

Response: "The University of Cádiz is carrying out a research project in the area of renewable energy, specifically on offshore wind energy. Would you like to know more details about any of these projects?"



Use of Tools

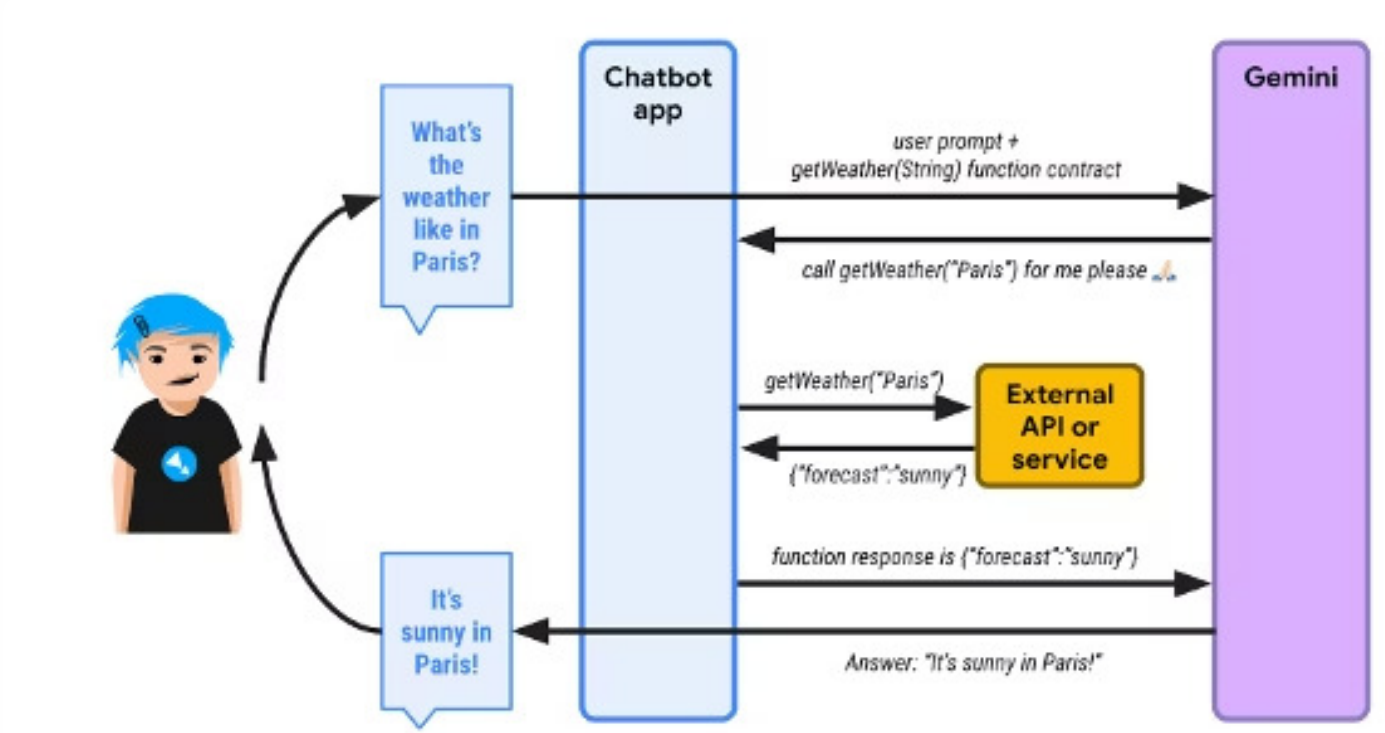
LLM with Functions

Large language models (LLMs) not only generate text, but can also execute actions, known as "plugins" or "tools".

However, not all large language models (LLMs) currently support this feature.

When invoking an LLM with these capabilities, the LLM does not directly call the tool, but instead indicates the intention to call it in its response, along with the necessary arguments.

Flow


What's the weather like in Paris?
Chatbot app
Gemini
user prompt + getWeather(String) function contract
call getWeather("Paris") for me please
getWeather("Paris")
External API or service
{"forecast":"sunny"}
function response is {"forecast":"sunny"}
It's sunny in Paris!
Answer: "It's sunny in Paris!"

Exposing Functions to the LLM

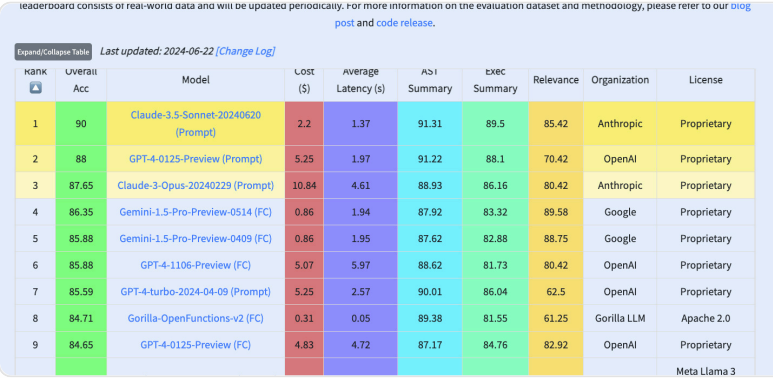
```
# This is the function that we want the model to be able to call
def get_delivery_date(order_id: str) -> datetime:
    # Connect to the database
    conn = sqlite3.connect('ecommerce.db')
    cursor = conn.cursor()
    # ...



# your function definition should be described using JSON Schema.
{
    "name": "get_delivery_date",
    "description": "Get the delivery date for a customer's order. Call this whenever you need to know the delivery date, for example when a customer asks 'Where is my package'",
    "parameters": {
        "type": "object",
        "properties": {
            "order_id": {
                "type": "string",
                "description": "The customer's order ID.",
            },
        },
        "required": ["order_id"],
        "additionalProperties": false,
    }
}
```

Berkeley Function Calling Leaderboard

This benchmark allows for an analysis to evaluate the performance of LLMs in terms of their ability to invoke external functions.



leaderboard consists of real-world data and will be updated periodically. For more information on the evaluation dataset and methodology, please refer to our blog post and code release.

Expand/Collapse Table *Last updated: 2024-06-22 [Change Log]*

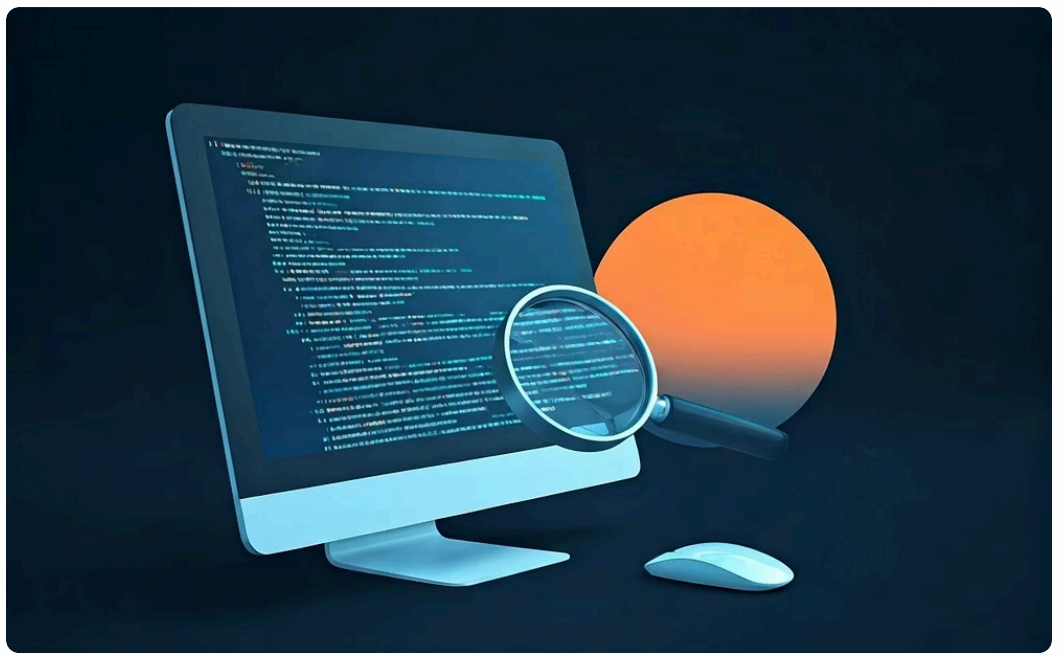
Rank	Overall Acc	Model	Cost ($)	Average Latency (s)	AST Summary	Exec Summary	Relevance	Organization	License
1	90	Claude-3.5-Sonnet-20240620 (Prompt)	2.2	1.37	91.31	89.5	85.42	Anthropic	Proprietary
2	88	GPT-4-0125-Preview (Prompt)	5.25	1.97	91.22	88.1	70.42	OpenAI	Proprietary
3	87.65	Claude-3-Opus-20240229 (Prompt)	10.84	4.61	88.93	86.16	80.42	Anthropic	Proprietary
4	86.35	Gemini-1.5-Pro-Preview-0514 (FC)	0.86	1.94	87.92	83.32	89.58	Google	Proprietary
5	85.88	Gemini-1.5-Pro-Preview-0409 (FC)	0.86	1.95	87.62	82.88	88.75	Google	Proprietary
6	85.88	GPT-4-1106-Preview (FC)	5.07	5.97	88.62	81.73	80.42	OpenAI	Proprietary
7	85.59	GPT-4-turbo-2024-04-09 (Prompt)	5.25	2.57	90.01	86.04	62.5	OpenAI	Proprietary
8	84.71	Gorilla-OpenFunctions-v2 (FC)	0.31	0.05	89.38	81.55	61.25	Gorilla LLM	Apache 2.0
9	84.65	GPT-4-0125-Preview (FC)	4.83	4.72	87.17	84.76	82.92	OpenAI	Proprietary
									Meta Llama 3

gorilla.cs.berkeley.edu

Berkeley Function Calling Leaderboard V2 (aka Berkeley Tool Calling L...

Explore The Berkeley Function Calling Leaderboard (also called The Berkeley Tool Calling Leaderboard) to see the LLM's ability to call functions (aka tools)...

Types of Actions

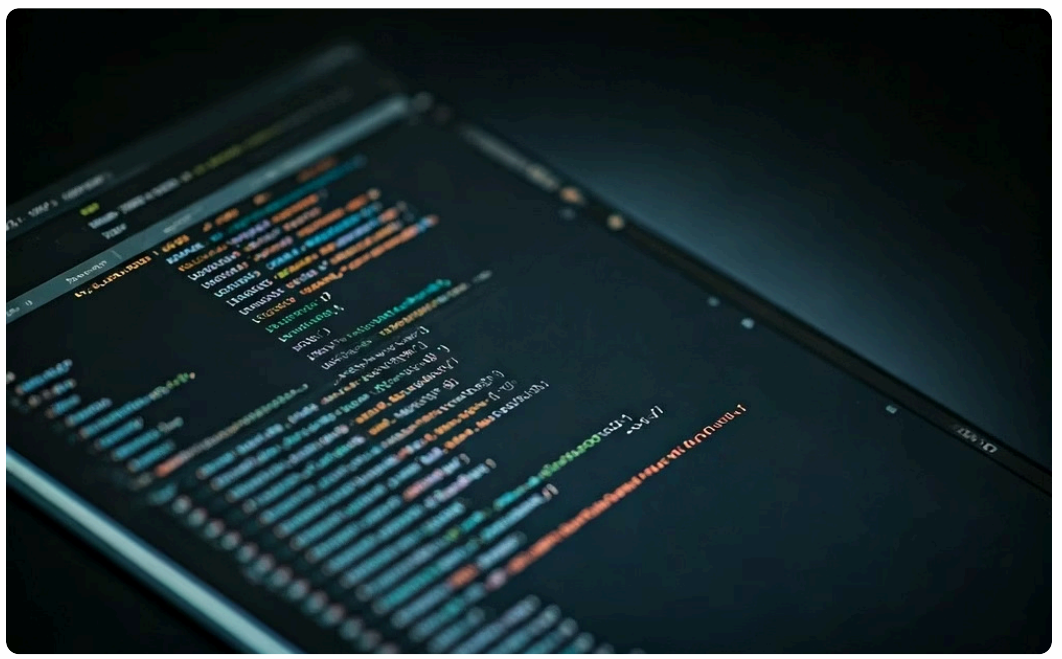


Invoke local functions

LLMs can interact with functions defined within the same environment.

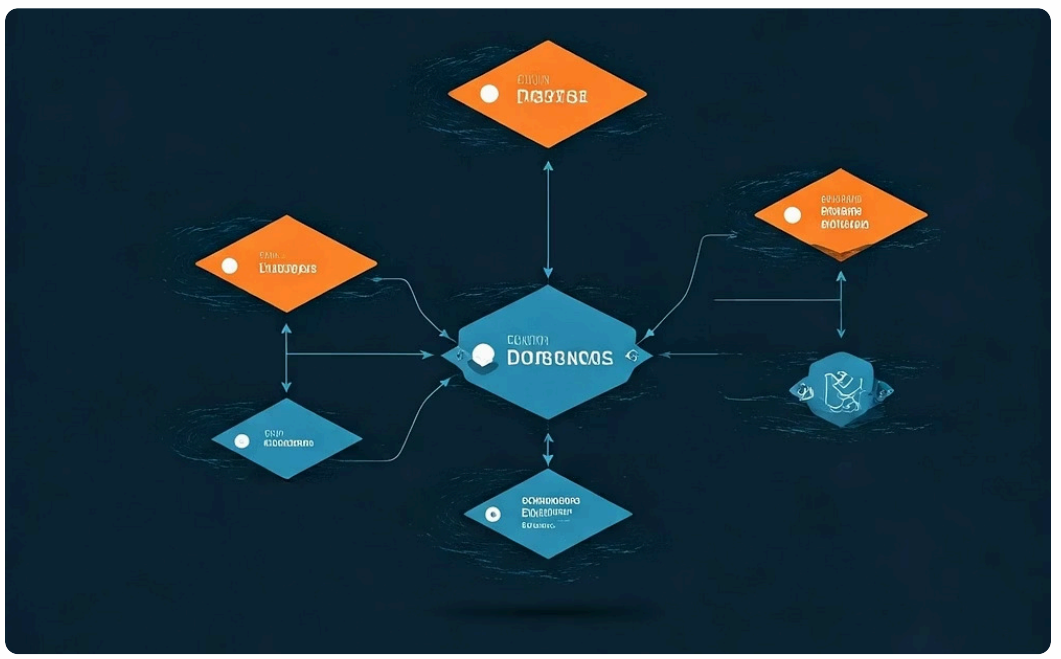
Invoke remote procedures

LLMs can execute tasks on external servers, accessing remote resources.



Generate and execute/interpret code

LLMs can generate code and execute/interpret programs in different programming languages.



Automate processes

LLMs can automate complex processes, combining different actions to complete specific tasks.

Example of a local procedure call

```
query = "What is 3 * 12? Also, what is 11 + 49?"

llm_with_tools.invoke(query).tool_calls
```

```
[{'name': 'multiply',
  'args': {'a': 3, 'b': 12},
  'id': 'call_1fyhJAbJHuKQe6n0PacubGsL',
  'type': 'tool_call'},
 {'name': 'add',
  'args': {'a': 11, 'b': 49},
  'id': 'call_fc2jVkKzwuPWyU7kS9qn1hyG',
  'type': 'tool_call'}]
```

```python
# The function name, type hints, and docstring are all part of the tool
# schema that's passed to the model. Defining good, descriptive schemas
# is an extension of prompt engineering and is an important part of
# getting models to perform well.
def add(a: int, b: int) -> int:
    """Add two integers.

    Args:
        a: First integer
        b: Second integer
    """
    return a + b


def multiply(a: int, b: int) -> int:
    """Multiply two integers.

    Args:
        a: First integer
        b: Second integer
    """
    return a * b
```

https://python.langchain.com/docs/how_to/tool_calling/

https://python.langchain.com/docs/how_to/custom_tools/

Invoking Remote Procedures

LLMs can access information and execute tasks in the real world through the invocation of remote procedures.

These invocations are carried out through APIs, such as the Moodle API, which allows obtaining information about virtual campus activities.

The LLM sends a request to the API, processes the received data and provides a response to the user.

Invoking Remote Procedures

1 Evaluate the Query

Analyse whether the user's query can be resolved using the documented API.

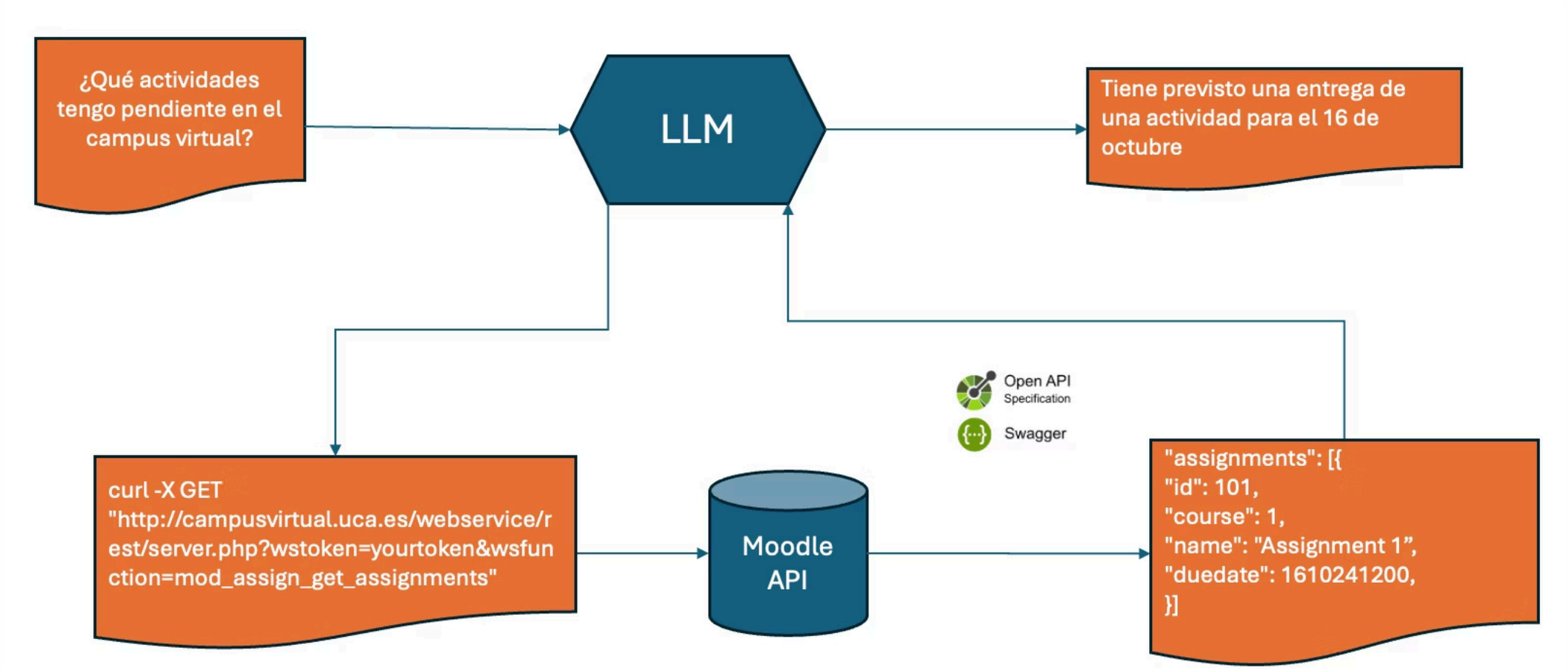
2 Generate an API Call Plan

If the query can be resolved, create a plan that describes each API call and its purpose.

3 Manage Sensitive Actions

If the plan includes a DELETE call, first request user authorisation.

Remote Procedure Call Invocation Flow



OpenAPI tool system prompt

You should:
1) Evaluate whether the user query can be solved by the API documented below. If no, say why.
2) If yes, generate a plan of API calls and say what they are doing step by step.
3) If the plan includes a DELETE call, you should always return a request for authorisation from the User first unless the User has specifically asked to delete something.

You should only use API endpoints documented below ("Endpoints you can use:").
You can only use the DELETE tool if the User has specifically asked to delete something. Otherwise, you should return a request for authorisation from the User first.
Some user queries can be resolved in a single API call, but some will require several API calls.
The plan will be passed to an API controller that can format it into web requests and return the responses.

Here are some examples:

Fake endpoints for examples:
GET /user to get information about the current user
GET /products/search search across products
POST /users/{{id}}/cart to add products to a user's cart
PATCH /users/{{id}}/cart to update a user's cart
PUT /users/{{id}}/coupon to apply idempotent coupon to a user's cart
DELETE /users/{{id}}/cart to delete a user's cart

Example of remote procedure call

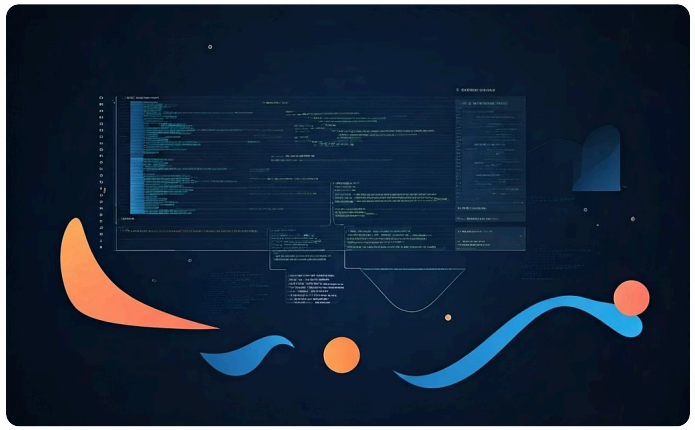
```
spotify_agent = planner.create_openapi_agent(
    spotify_api_spec,
    requests_wrapper,
    llm,
    allow_dangerous_requests=ALLOW_DANGEROUS_REQUEST,
)
user_query = (
    "make me a playlist with the first song from kind of blue. call it machine
blues."
)
spotify_agent.invoke(user_query)
```

https://python.langchain.com/docs/integrations/tools/openapi/

Generate and interpret code

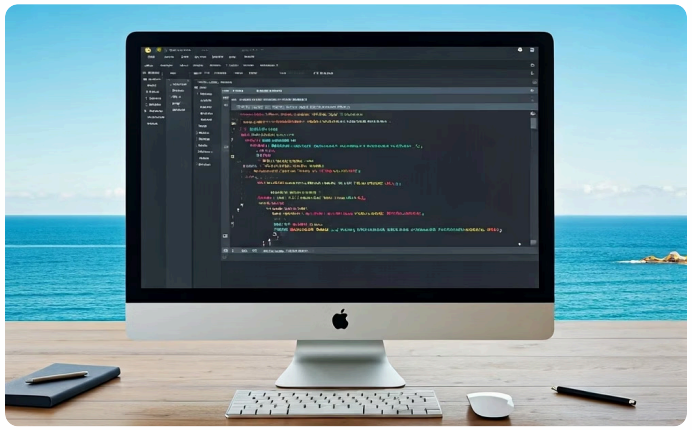
Code execution

LLMs can generate code in various programming languages, such as Python, Java, and JavaScript.



Code interpretation

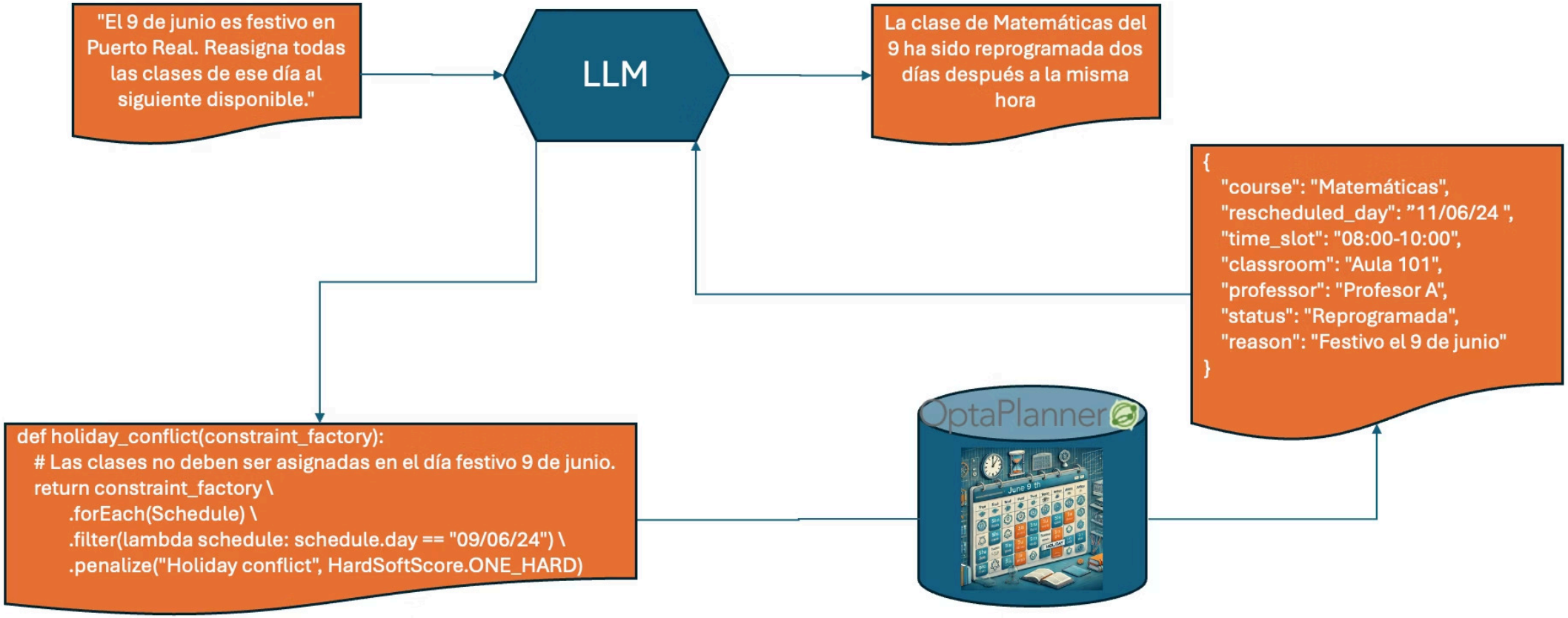
They can interpret and execute code in real-time in a protected environment, offering a more dynamic way of working with applications.



Interaction with business logic

They can interact with existing systems through code, automating tasks and simplifying complex processes.

Flow


"El 9 de junio es festivo en Puerto Real. Reasigna todas las clases de ese día al siguiente disponible."
LLM
La clase de Matemáticas del 9 ha sido reprogramada dos días después a la misma hora
{
"course": "Matemáticas",
"rescheduled_day": "11/06/24 ",
"time_slot": "08:00-10:00",
"classroom": "Aula 101",
"professor": "Profesor A",
"status": "Reprogramada",
"reason": "Festivo el 9 de junio"
}
def holiday_conflict(constraint_factory):
# Las clases no deben ser asignadas en el día festivo 9 de junio.
return constraint_factory \
.forEach(Schedule) \
.filter(lambda schedule: schedule.day == "09/06/24") \
.penalize("Holiday conflict", HardSoftScore.ONE_HARD)
OptaPlanner
June 9 th

Example of code generation and interpretation

```
python_repl = PythonREPL()
```

```
python_repl.run("print(1+1)")
```

```
Python REPL can execute arbitrary code. Use with caution.
```

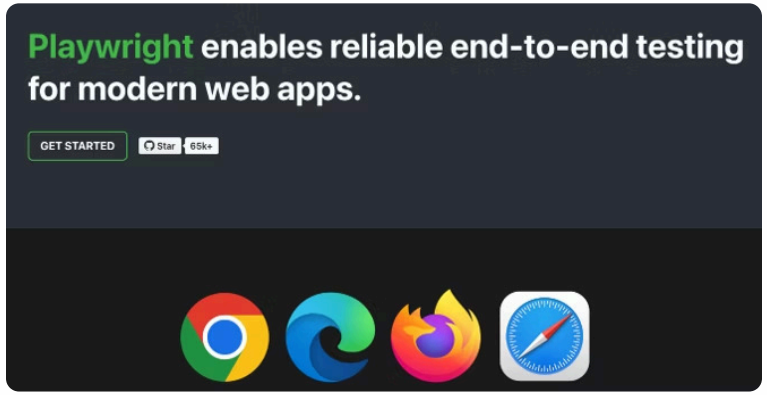
```
'2\n'
```

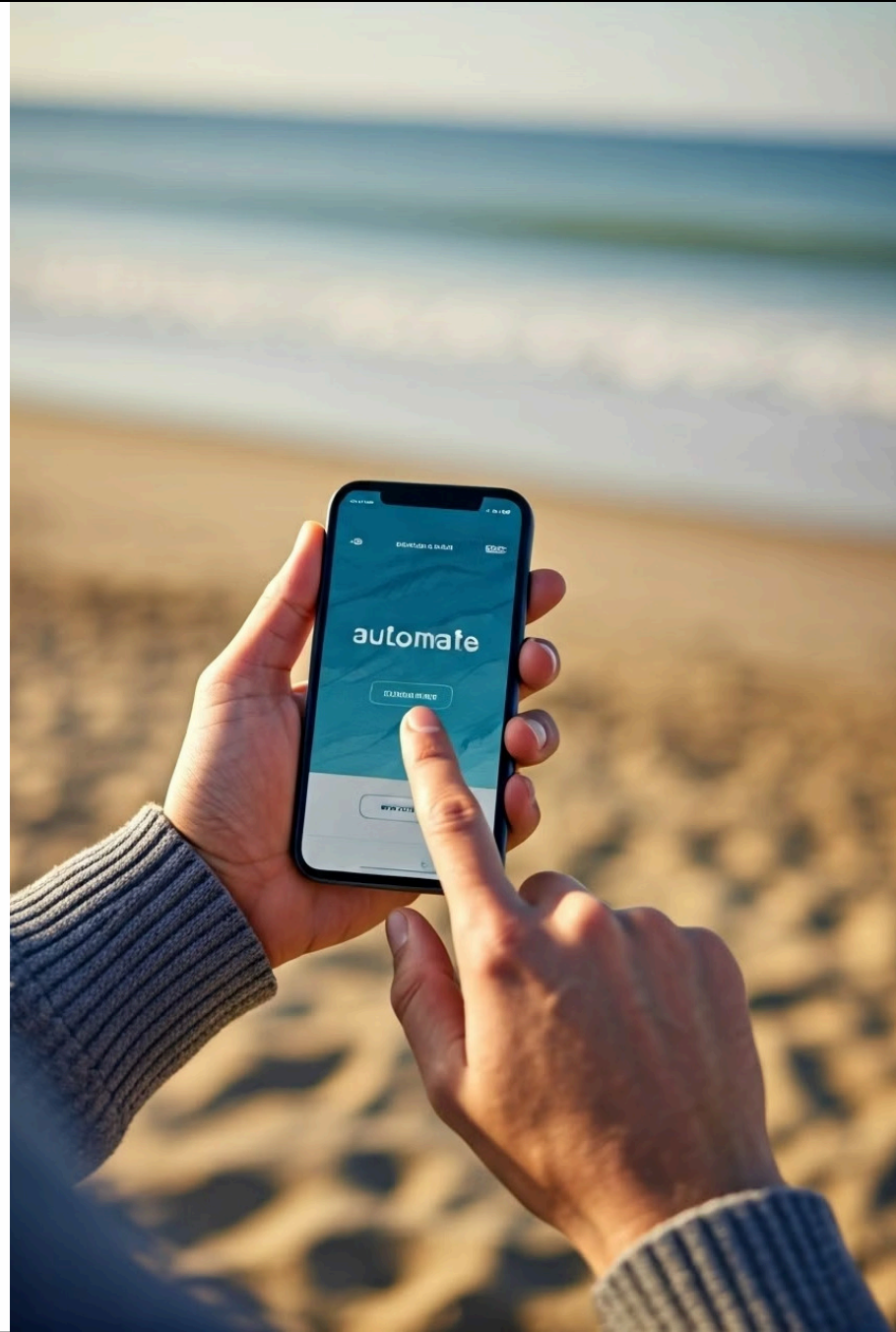
```
# You can create the tool to pass to an agent
repl_tool = Tool(
    name="python_repl",
    description="A Python shell. Use this to execute python commands. Input
should be a valid python command. If you want to see the output of a value, you
should print it out with `print(...)`.",
    func=python_repl.run,
)
```

https://python.langchain.com/docs/integrations/tools/#code-interpreter

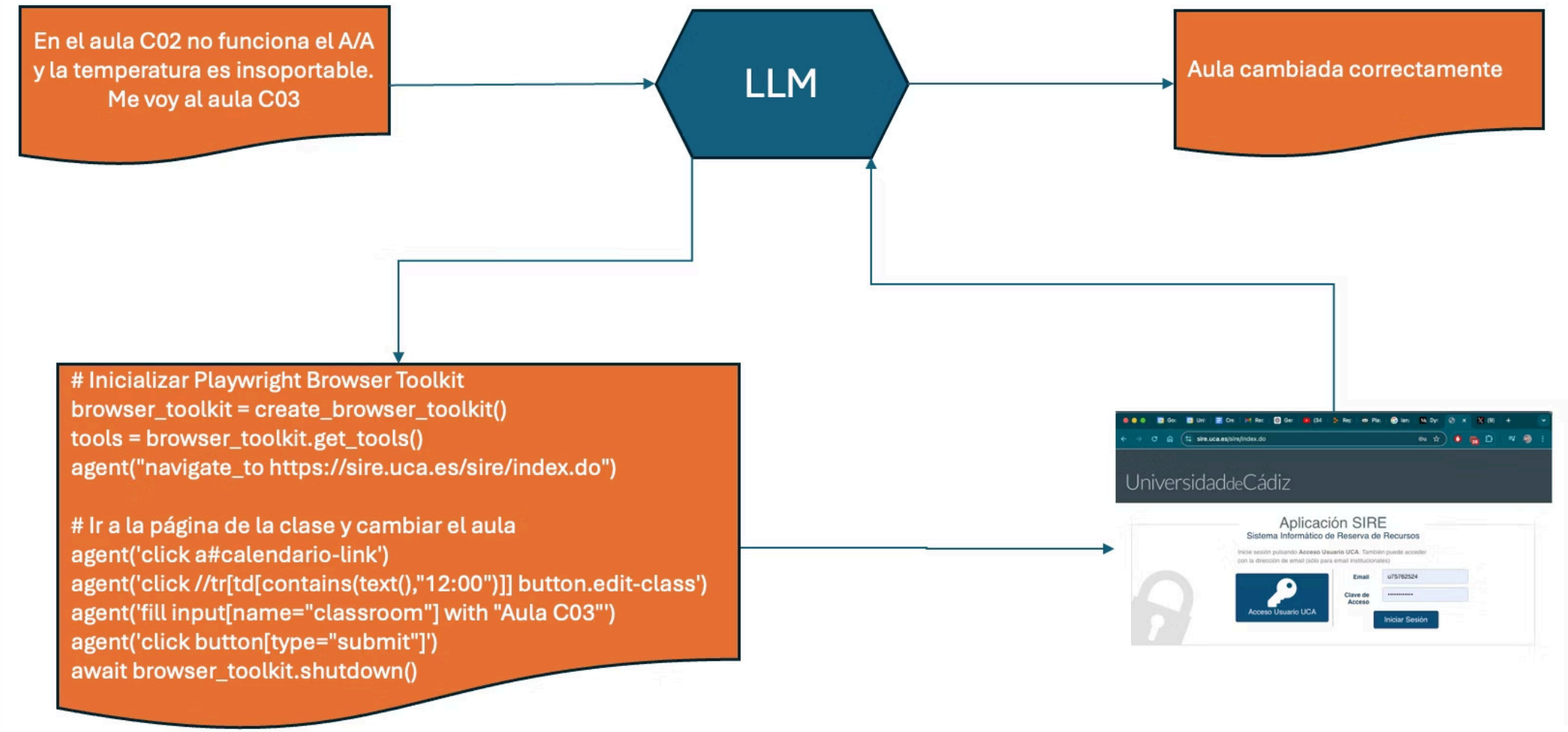
Automating processes

LLMs are capable of triggering the execution of task automation scripts. Libraries like Playwright enable interaction with a web browser for the retrieval and submission of data through its interface.





Flow


En el aula C02 no funciona el A/A y la temperatura es insoportable. Me voy al aula C03
LLM
Aula cambiada correctamente
# Inicializar Playwright Browser Toolkit
browser_toolkit = create_browser_toolkit()
tools = browser_toolkit.get_tools()
agent("navigate_to https://sire.uca.es/sire/index.do")
# Ir a la página de la clase y cambiar el aula
agent('click a#calendario-link')
agent('click //tr[td[contains(text(),"12:00")]] button.edit-class')
agent('fill input[name="classroom"] with "Aula C03"')
agent('click button[type="submit"]')
await browser_toolkit.shutdown()
UniversidadDeCádiz
Aplicación SIRE
Sistema Informático de Reserva de Recursos
Acceso Usuario UCA
Email
Clave de Acceso
Iniciar Sesión

Example of automation in the browser

```
async_browser = create_async_playwright_browser()
toolkit = PlayWrightBrowserToolkit.from_browser(async_browser=async_browser)
tools = toolkit.get_tools()
tools
```

```
[ClickTool(async_browser=<Browser type=<BrowserType name=chromium executable_path=
 NavigateTool(async_browser=<Browser type=<BrowserType name=chromium executable_pa
 NavigateBackTool(async_browser=<Browser type=<BrowserType name=chromium executab
 ExtractTextTool(async_browser=<Browser type=<BrowserType name=chromium executable
 ExtractHyperlinksTool(async_browser=<Browser type=<BrowserType name=chromium exec
 GetElementsTool(async_browser=<Browser type=<BrowserType name=chromium executable
 CurrentWebPageTool(async_browser=<Browser type=<BrowserType name=chromium executa
```

```
result = await agent_chain.arun("What are the headers on langchain.com?")
print(result)
```

https://python.langchain.com/docs/integrations/tools/playwright/

Ex 1. Creating a copilot

Collaboration Between Agents

Considerations When Working with Complex Agents

Multiple Scenarios

Attempting to cover all cases in a single prompt often generates suboptimal results. It is better to segment and specialise.

Additional Information

It is not always necessary to provide extra data to the LLM in each iteration. This can increase costs and reduce efficiency.

Access to Tools

Limiting the LLM's access to specific tools improves the security and efficiency of the system.

Balancing Creativity

The LLM's temperature should be adjusted according to the task: low for precision, high for creativity.

Divide and Conquer

Diverse Skills

Each agent specialises in a specific task, which optimises their performance through customised prompts.

Different LLMs

The most suitable language model is selected for each task, which improves the overall efficiency of the system.

Controlled Access

Tools and information retrievers are strategically assigned to each agent, which increases security and performance.

Chaining of Agents

Sequential Execution

Agents operate in series, passing results from one to another for complex tasks.

Conditional Execution

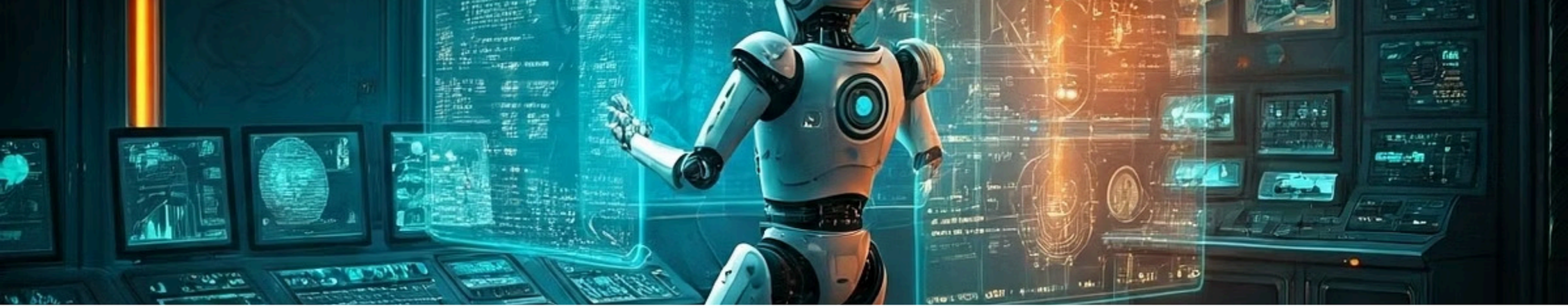
Decision logics are implemented to activate specific agents based on the circumstances.

Iterative Execution

Loops allow refining results or processing large data volumes efficiently.

Developer Control

The programmer maintains control of the flow, integrating LLMs as modular components.



Autonomous Agents

Full Autonomy

LLMs drive the application, making complex decisions without constant human intervention.

Hierarchy of Agents

Agents can act as tools for others, creating highly sophisticated systems.

Advanced Systems

Include loops, conditions and persistence for complex tasks and continuous learning.

Human-in-the-loop

The option of human supervision to approve or cancel critical actions is maintained.

Workflows

Tools and frameworks, such as LangGraph, are emerging that allow modelling agents through flow diagrams

Architectural Self-reflection

Reasoning Analysis

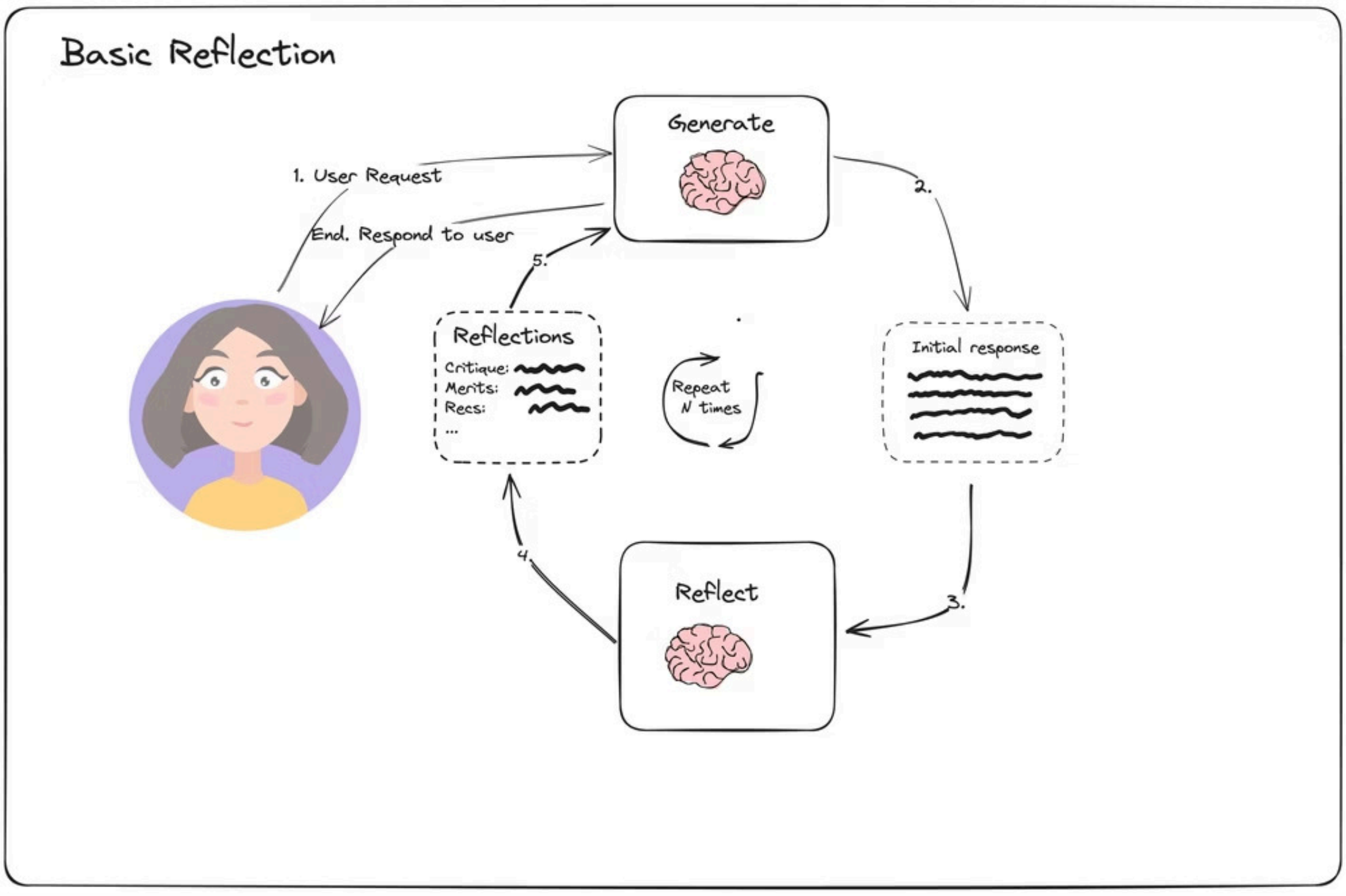
The LLM examines its own traces of reasoning, to detect errors or inconsistencies.

Strategy Adjustment

Based on the reflection, the agent modifies its approach for future actions.

Continuous Improvement

This cycle allows for constant evolution of the agent, increasing its effectiveness.



https://blog.langchain.dev/reflection-agents/

Plan-and-Execute Architecture

Planner

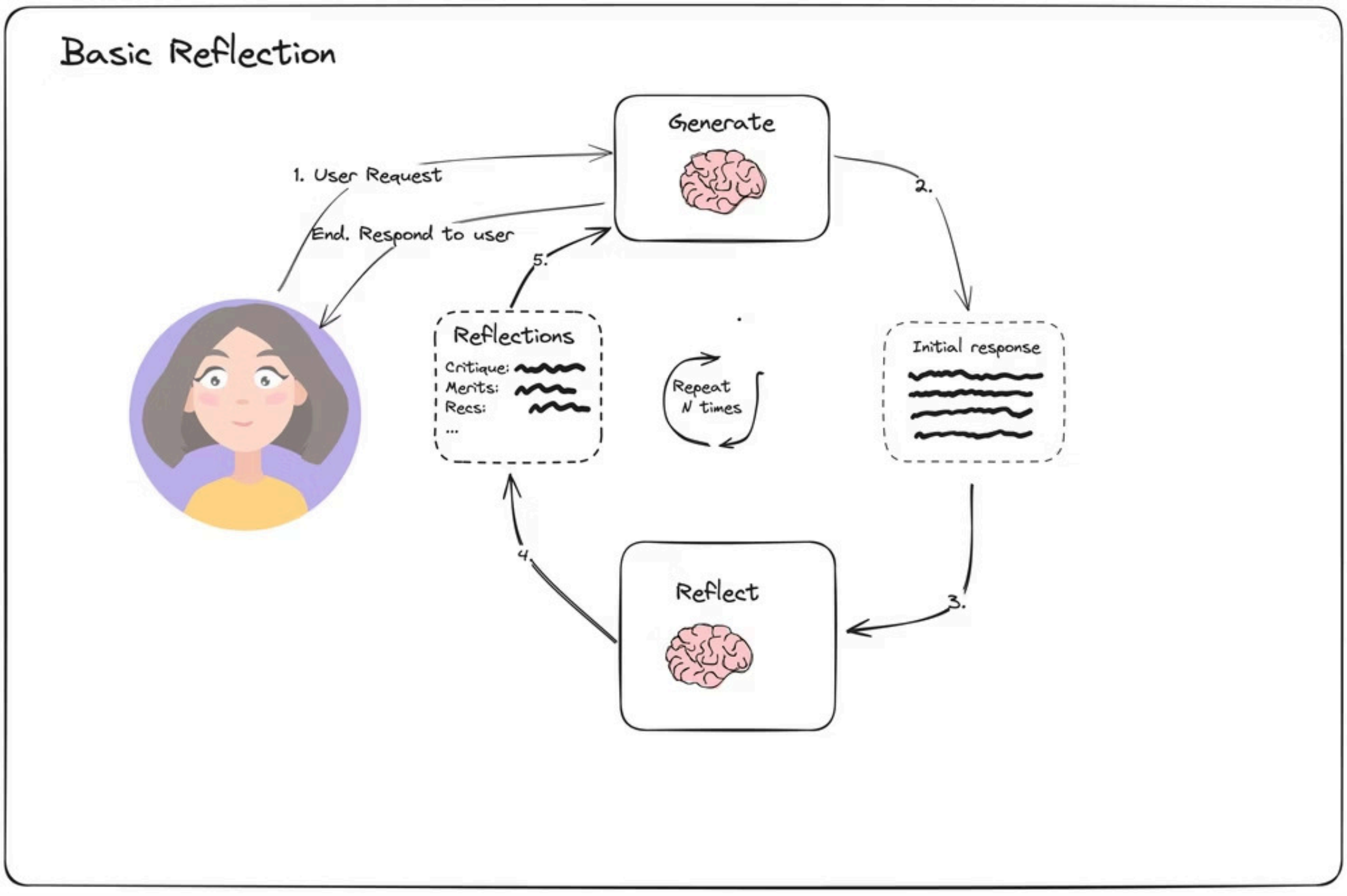
Responsible for sending a prompt to the LLM to generate a multi-step plan

Executor

Executes each step of the plan using specific tools to perform the action.

Planning Agents

There are other architectures with similar purposes: ReAct, ReWOO, LLM Compiler



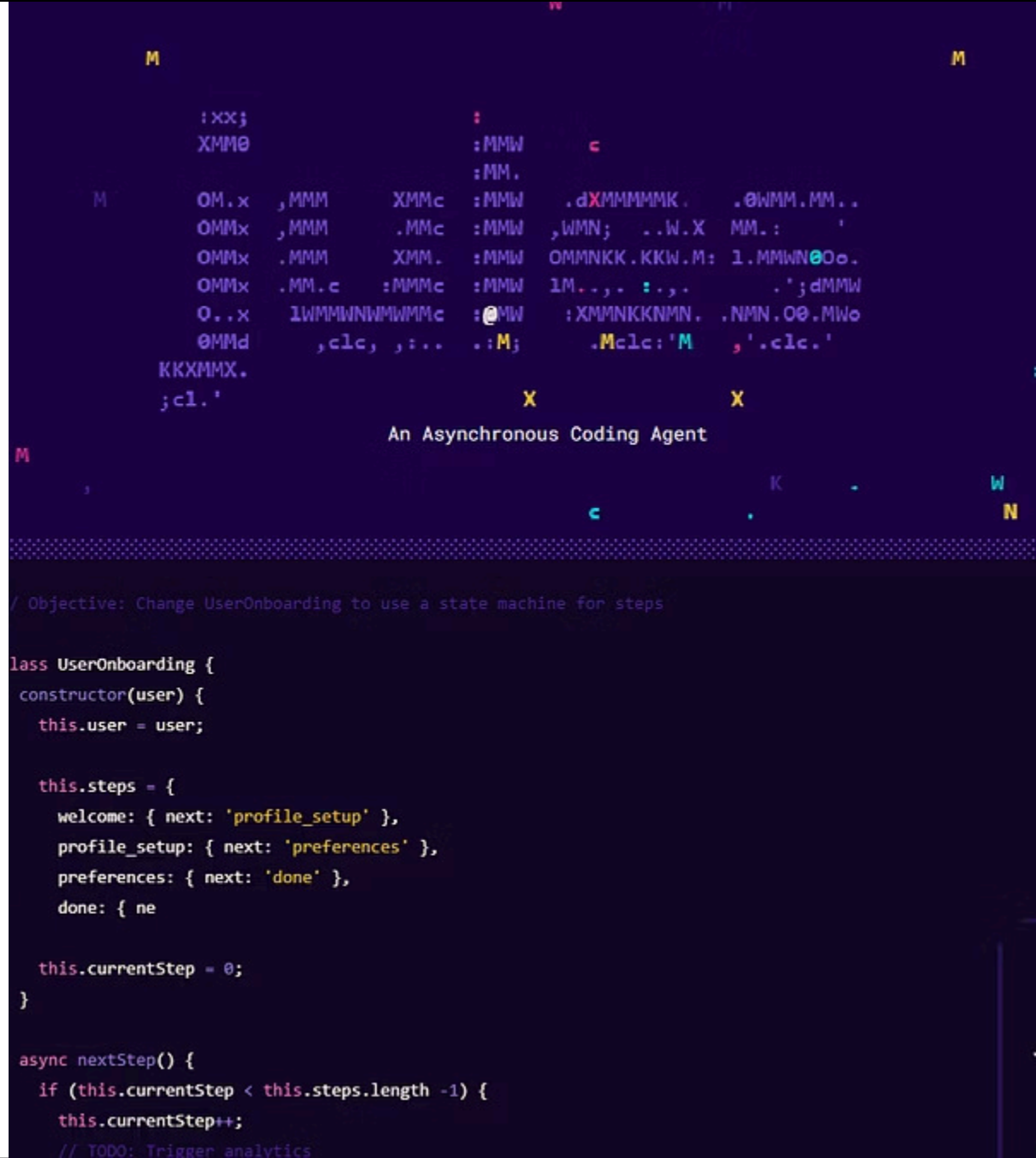
https://blog.langchain.dev/planning-agents/

IDEs for Agentic AI

Jules (Google)

Jules is an **asynchronous coding agent** powered by Gemini 2/2.5, designed to handle multi-step tasks in your codebase.

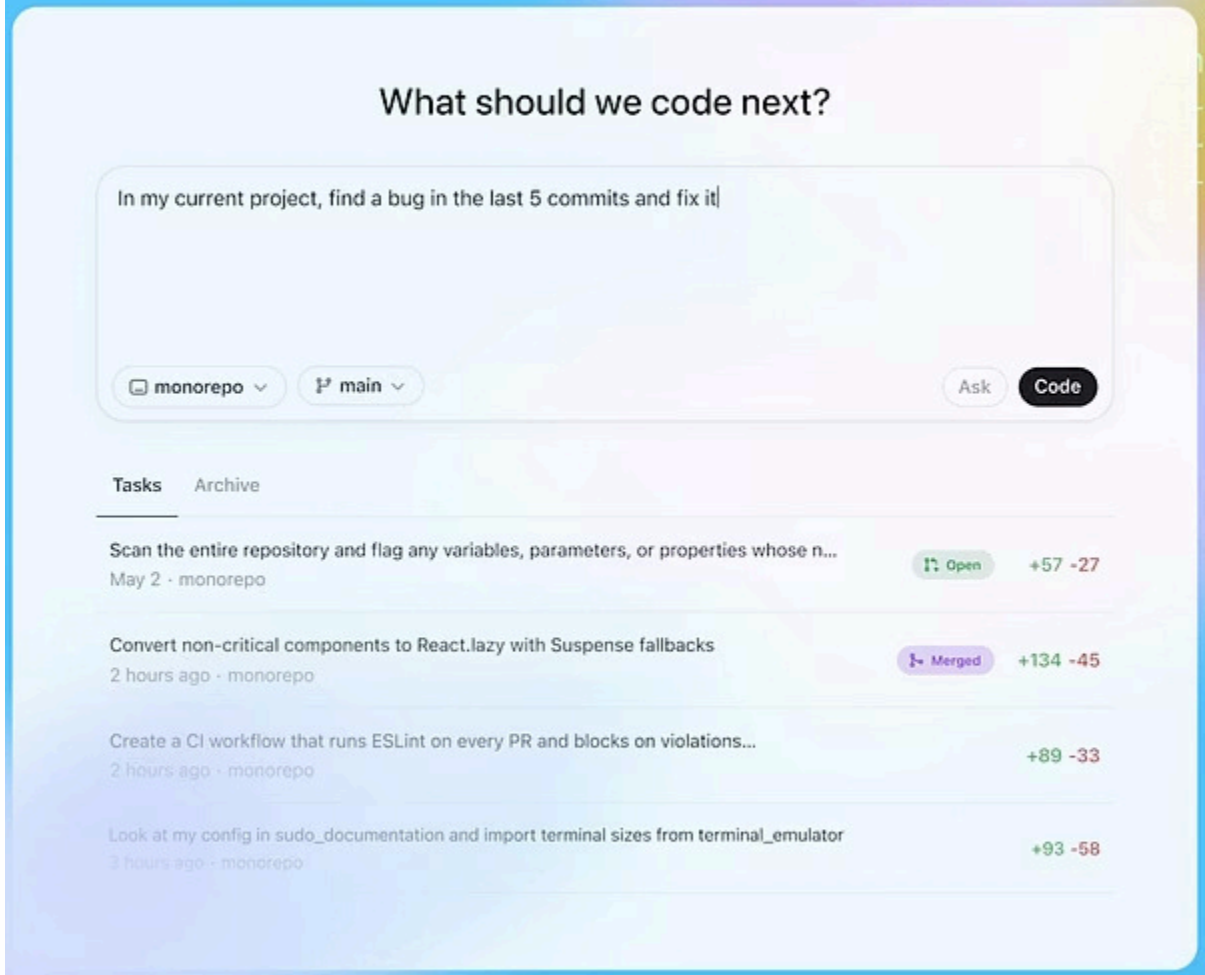
- **Context-aware**: clones your repo into a secure Google Cloud VM to fully understand project structure
- **0Task automation**: writes tests, fixes bugs, bumps dependencies, builds features
- **Workflows**: accepts prompts or issue labels, providing summaries and pull request patches



Codex Agent (OpenAI)

Codex is a **cloud-based multi-task software engineering agent** available from within ChatGPT.

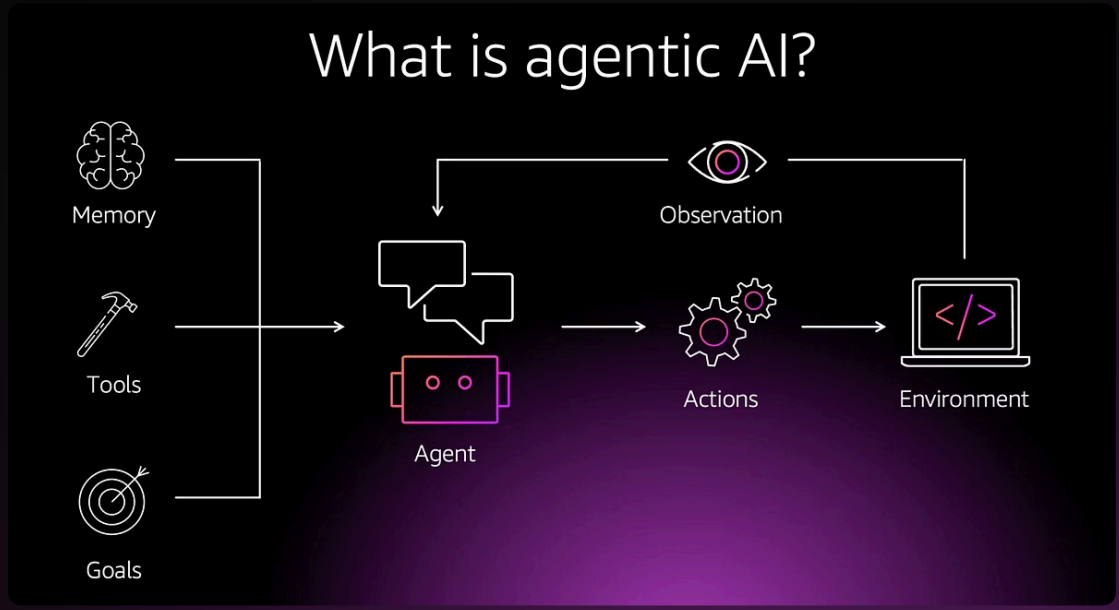
- Works across **multiple sandboxed tasks** simultaneously
- Can **write features, fix bugs, propose PRs, run tests iteratively**
- **Available** to ChatGPT Pro, Team, Enterprise now; soon Plus/Edu p
- Also offers an **open-source CLI agent** for local repo interaction



AWS Agentic AI (Amazon)

Amazon Q Developer brings **agentic coding** directly into IDEs like VS Code, JetBrains, etc.

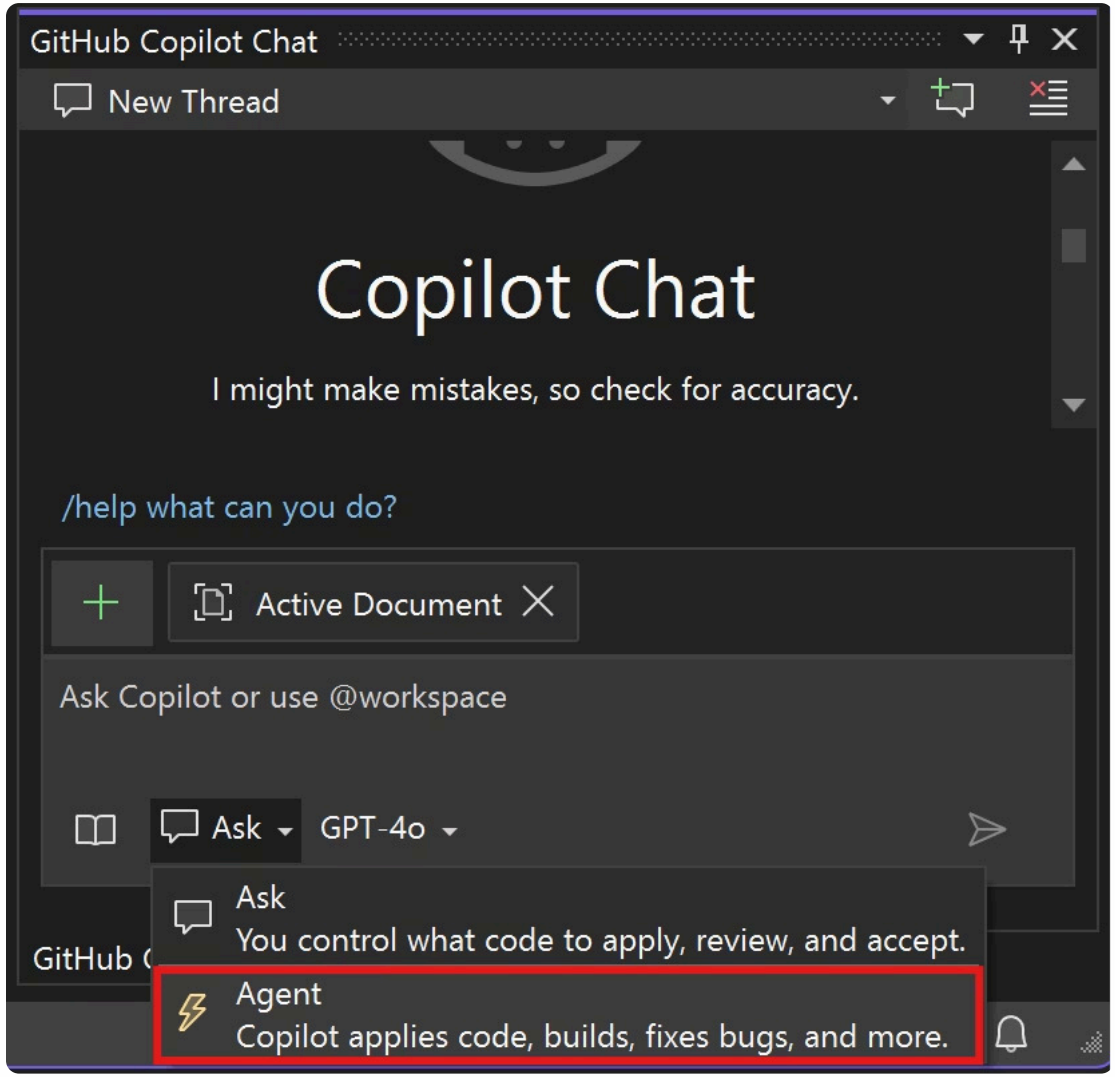
- Integrates in-IDE **agent chat + local file execution + AWS CLI access**
- Supports **switching between planning chat and build-time actions**
- Can read/write files, run shell commands, query AWS resources (e.g., list S3 buckets)



GitHub Copilot Agent Mode (Microsoft)

Copilot Agent Mode elevates Copilot to a **fully autonomous coding agent** integrated with GitHub Actions.

- Triggered by assigning issues or toggling Agent Mode in IDE
- Clones repo in GitHub Actions VM, analyzes code, implements changes, iterates until completion
- Generates draft PR with commit history, logs its reasoning, reacts to repo activity



OK, but are there any free IDEs to test?

"Free" IDEs

Replit Agent – Browser-based AI agent platform

- Web IDE + **natural-language agent** that builds apps or scripts
- Free tier supports basic functionality; paid plans unlock advanced features
- Enables describing app in natural language → generates working code
- Ideal for rapid prototyping, especially in educational settings

Replit

Replit – Build apps and sites wi...

Replit is an AI-powered platform for building professional web apps and...

CodingGenie (Open-Source)

- A proactive LLM-powered programming assistant
- 🚀 **Open-source** and free: GitHub repo available (Apache-2.0)
- Context-aware suggestions (bugs, tests, features) **proactively offered**
- Demo videos + docs included; designed to integrate into local IDEs

CodingGenie

CodingGenie

A Proactive LLM-Powered Programming Assistant

PearAI

Open-source AI code editor

- Features include **AI chat**, debugging, and context-aware coding
- Router selects best-performing coding models automatically
- Downloadable with free features; may offer premium enhancements later

trypear.ai

PearAI – The AI Code Editor Fo...

PearAI is an open source AI code editor with powerful features like AI...

Summary

This presentation has explored the landscape of LLM agents, from their origins to the present day.

We have delved into the growing autonomy of agents, examining architectures such as reflection and planning-execution.

The tools and platforms that enable the development and application of LLM agents have been highlighted.