

Agents, Assemble!

GenAI on steroids with Autogen and
multi agents

Simone Colucci
Riccardo Zoncada

Agenda

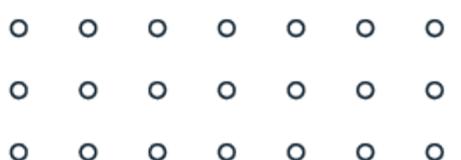
- Use case
- AI agents & multi-agent paradigm
- AutoGen & AutoGen Studio
- Live experimentations
- Wrap up

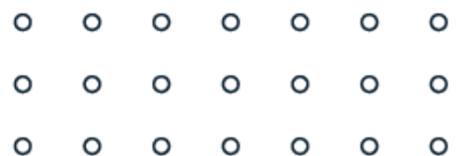
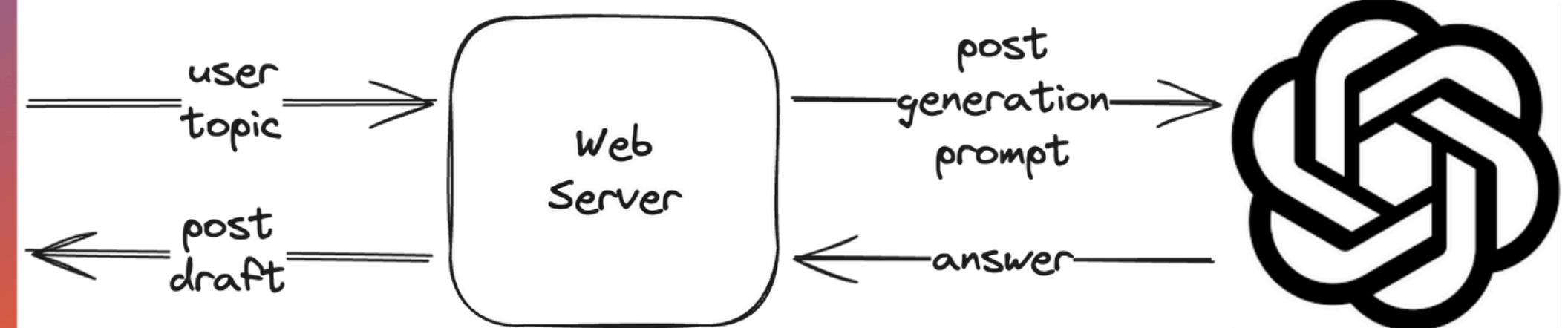
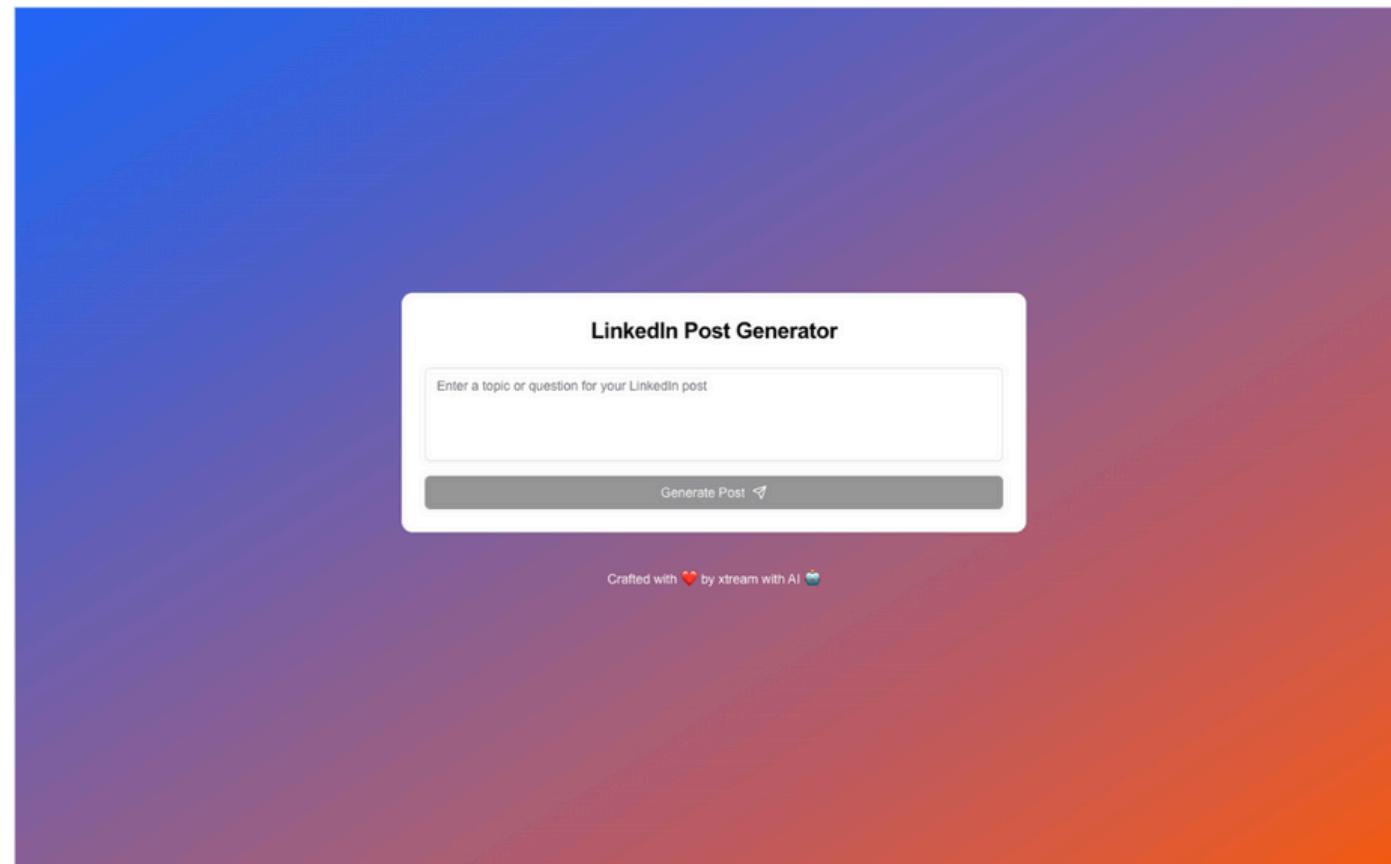
LinkedIn Post Generator

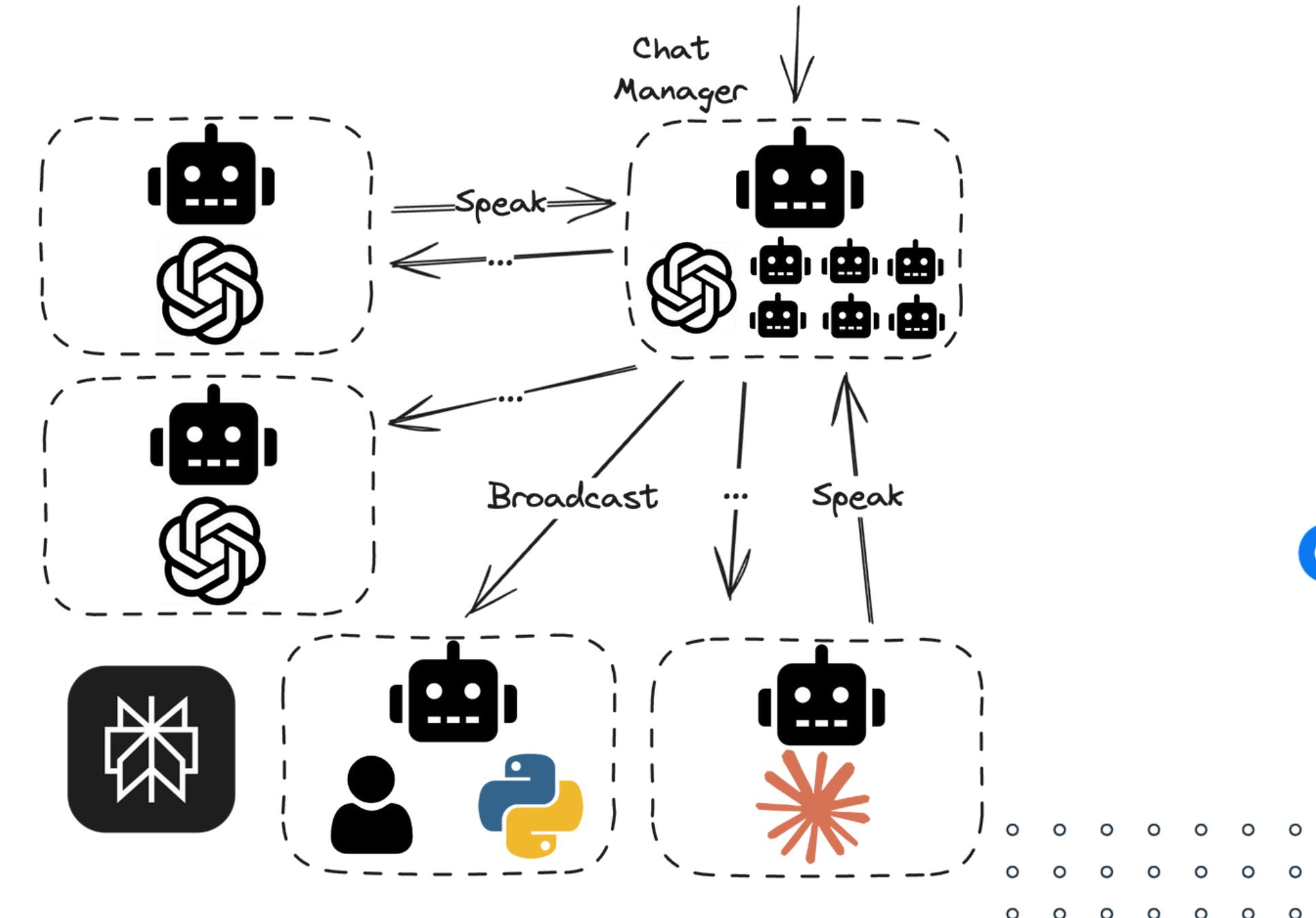
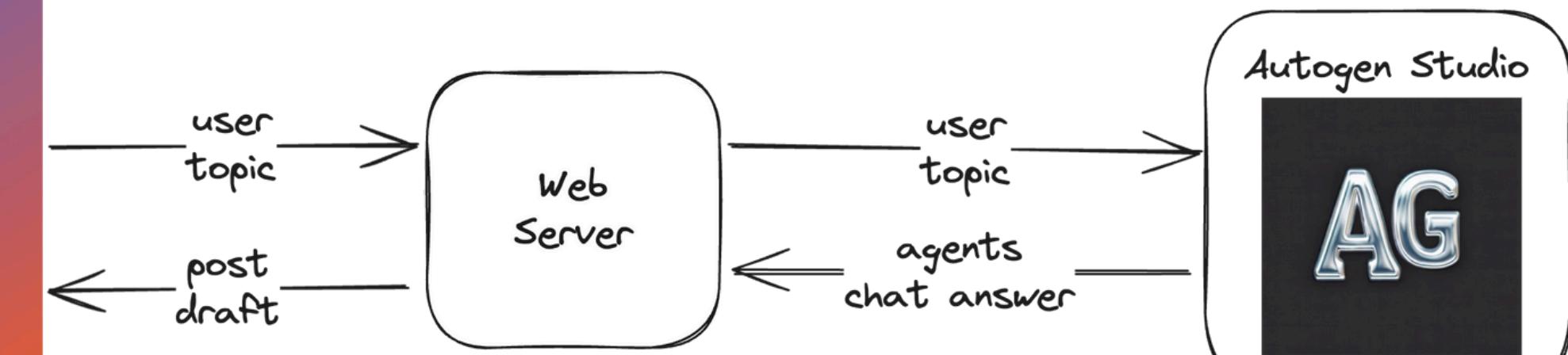
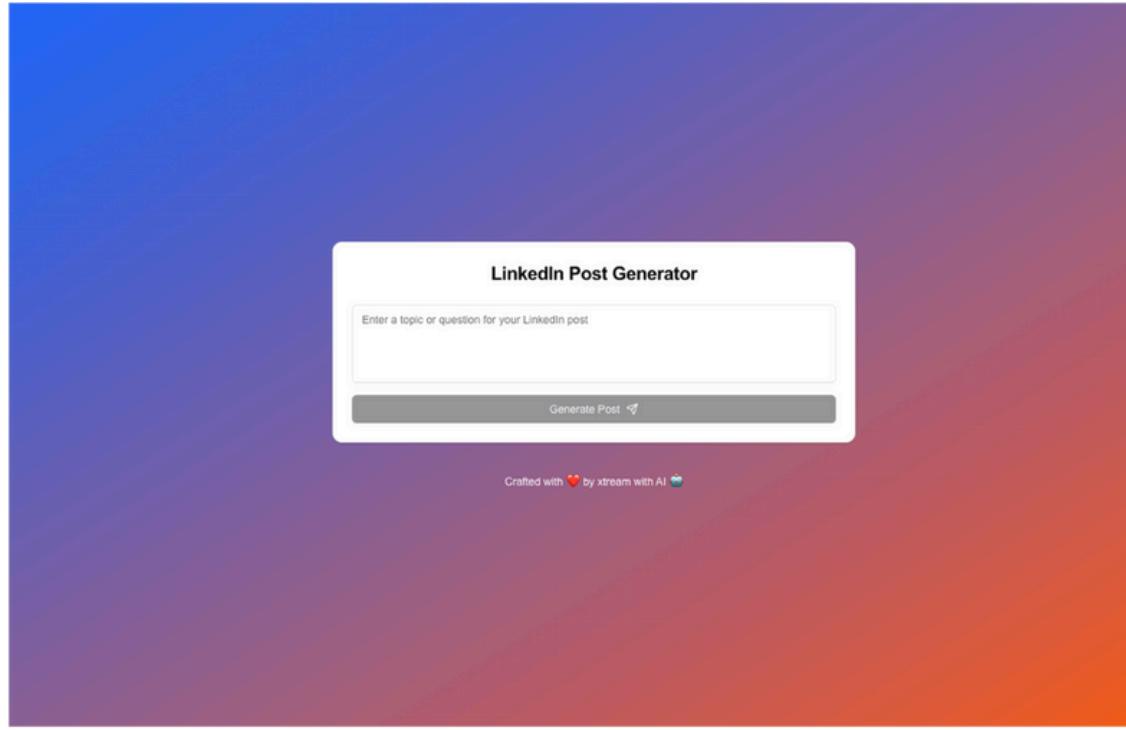
Enter a topic or question for your LinkedIn post

Generate Post ➡

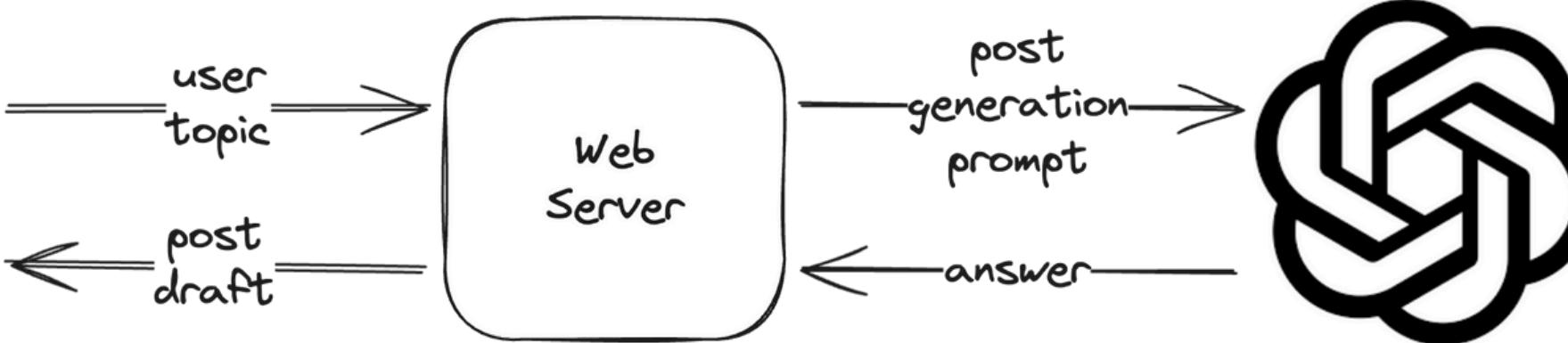
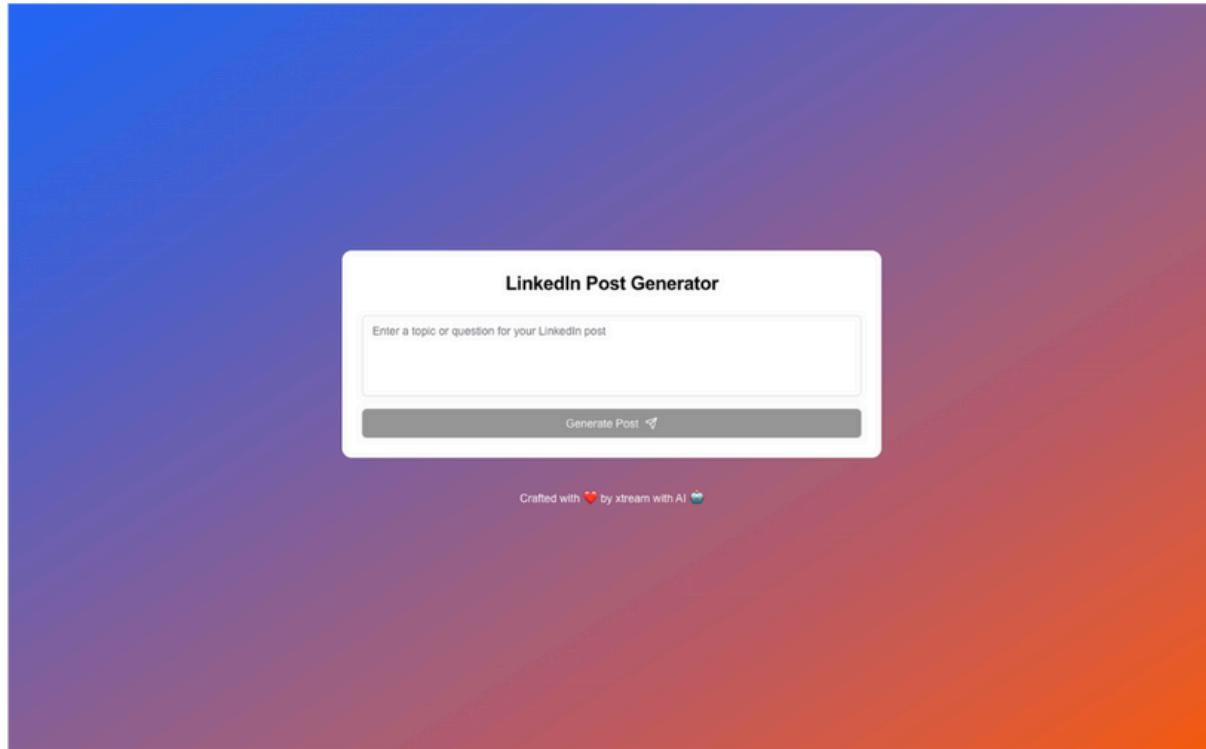
Crafted with ❤️ by xtream with AI 🤖







Single LLM – one-shot prompt



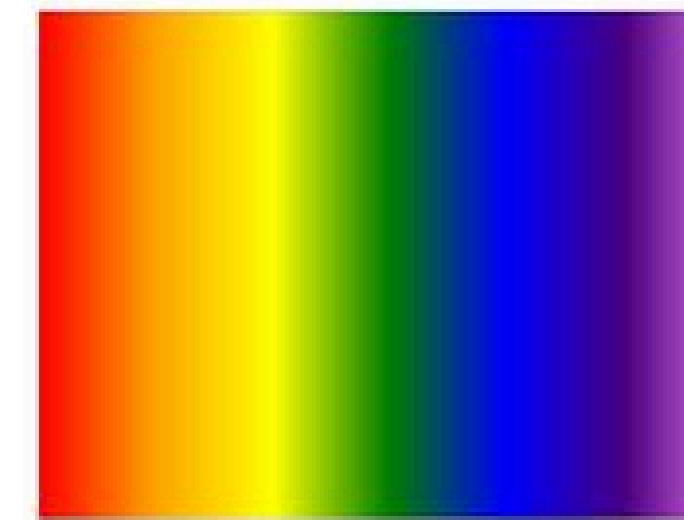
- Weak guarantee on enforcing prompt guidelines
- Risk of hallucinations on unknown topics
- Lacks reasoning capabilities

Linear Gradients



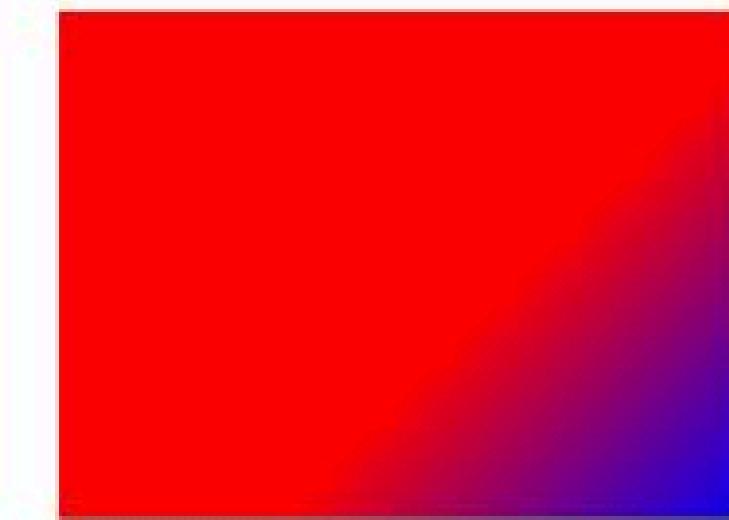
```
background: linear-gradient(to bottom right, red, rgba(255,0,0,0));
```

Linear with transparency



```
background: linear-gradient(to right, red, orange, yellow, green, blue, indigo, violet);
```

Gradient with multiple color stops



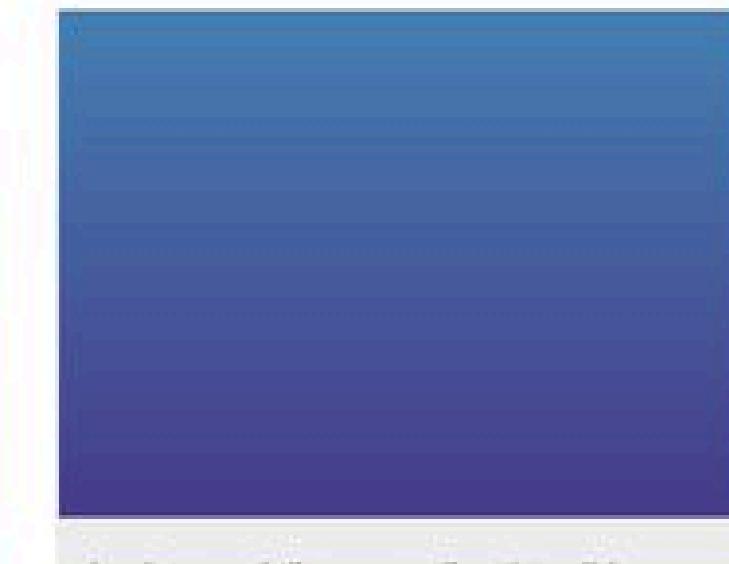
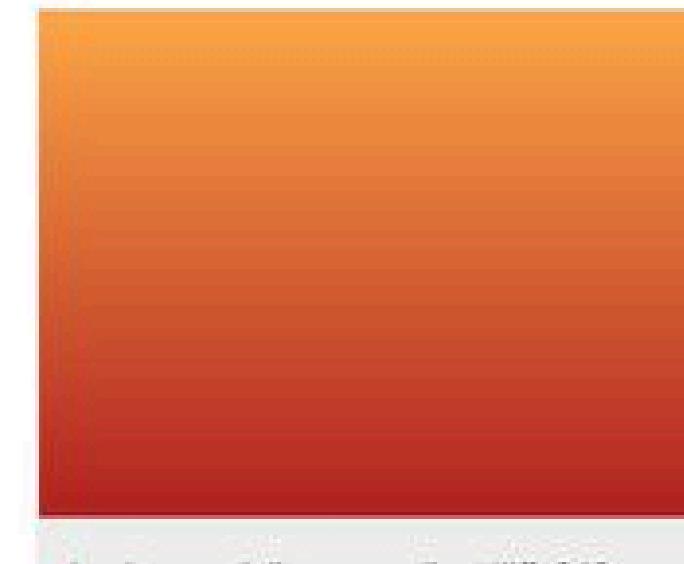
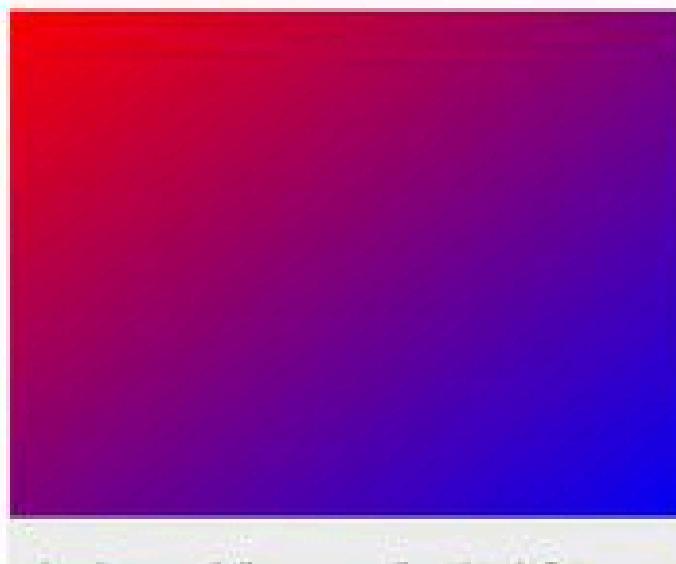
```
background: linear-gradient(135deg, red, red 60%, blue);
```

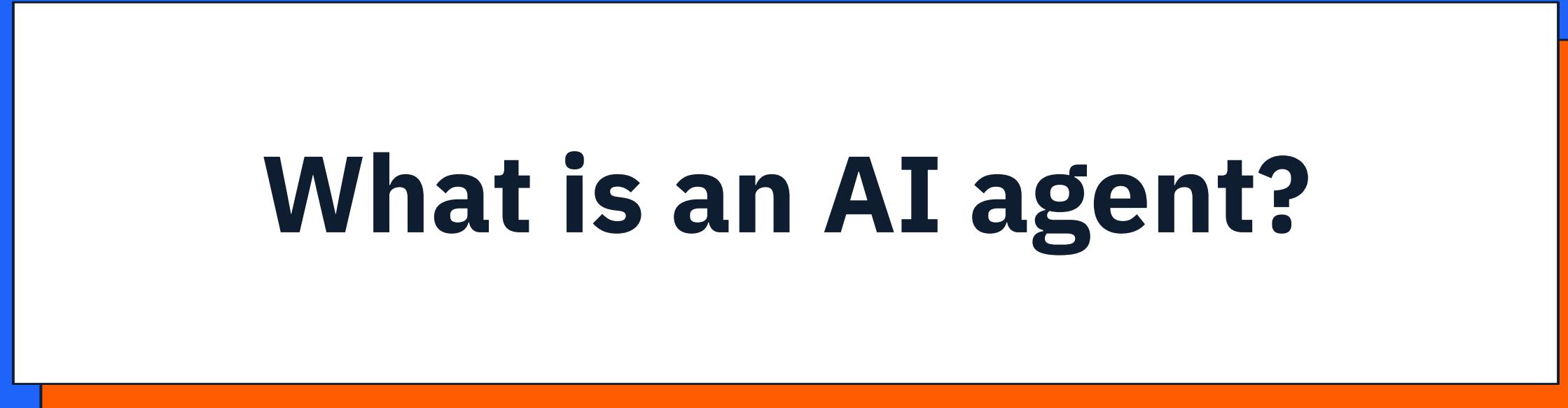
Gradient that starts at 60% of the gradient line



```
background: linear-gradient(135deg, red, blue);
```

Gradient at a 45 degree angle



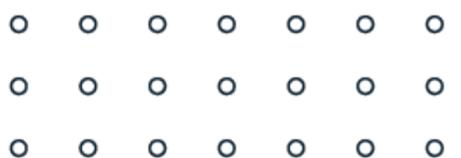
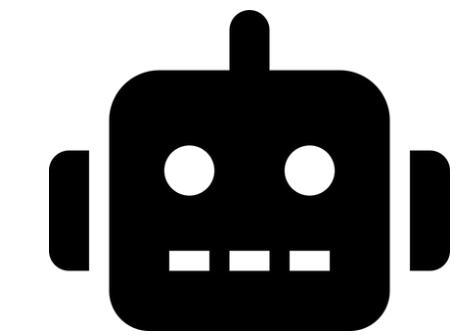


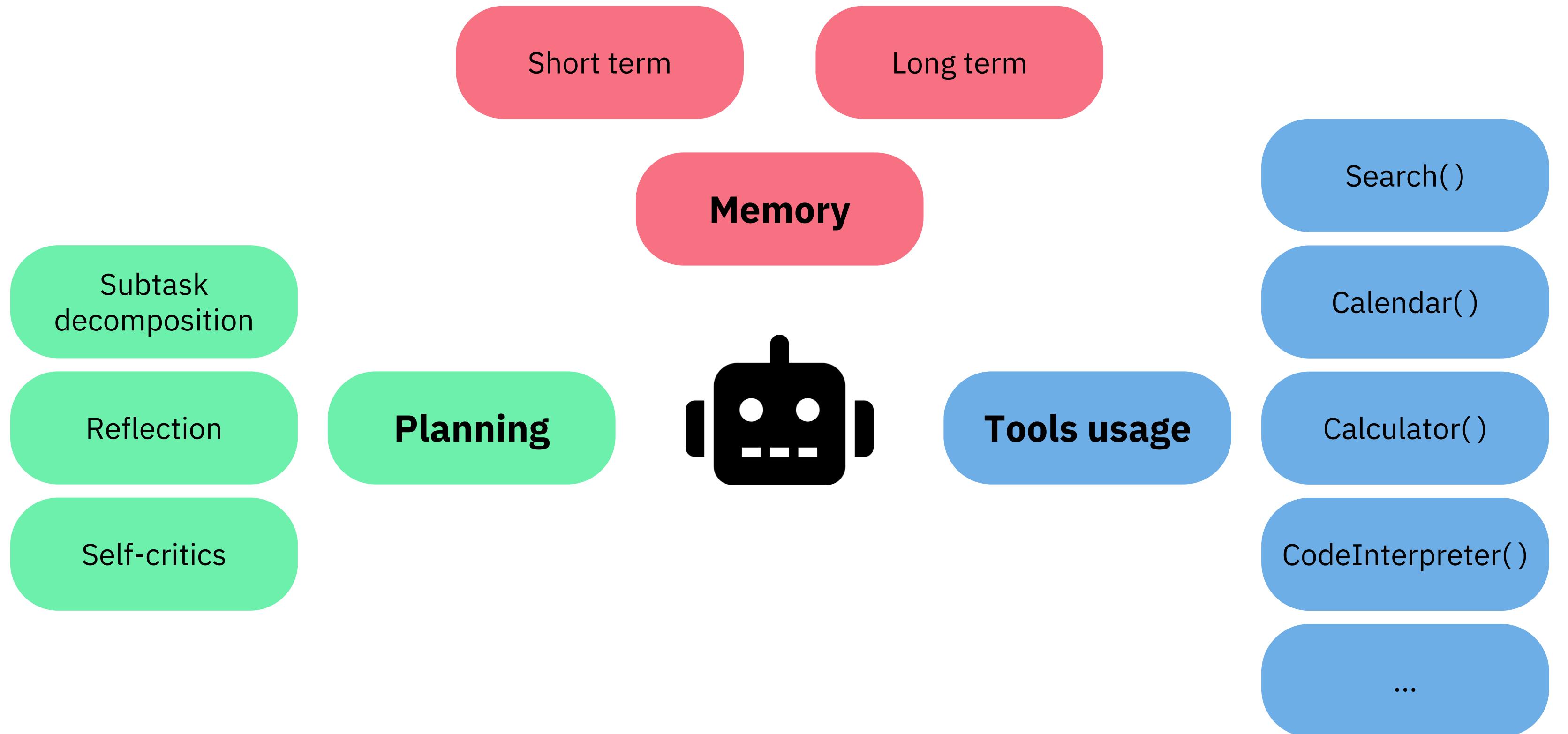
What is an AI agent?

Planning

Memory

Tools usage





Why multi-agent?

Multi-agent approach

- Multiple agents with their own strategies and behaviors.
- Every agent could use a specialised LLMs, tailored for a specific task.
- Communicate and collaborate to handle more dynamic and complex tasks in a collective decision-making processes.
- Empirical studies demonstrate the effectiveness of the framework in many example applications.

AgentCoder: Multi-Agent Code Generation with Effective Testing and Self-optimisation

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Abstract

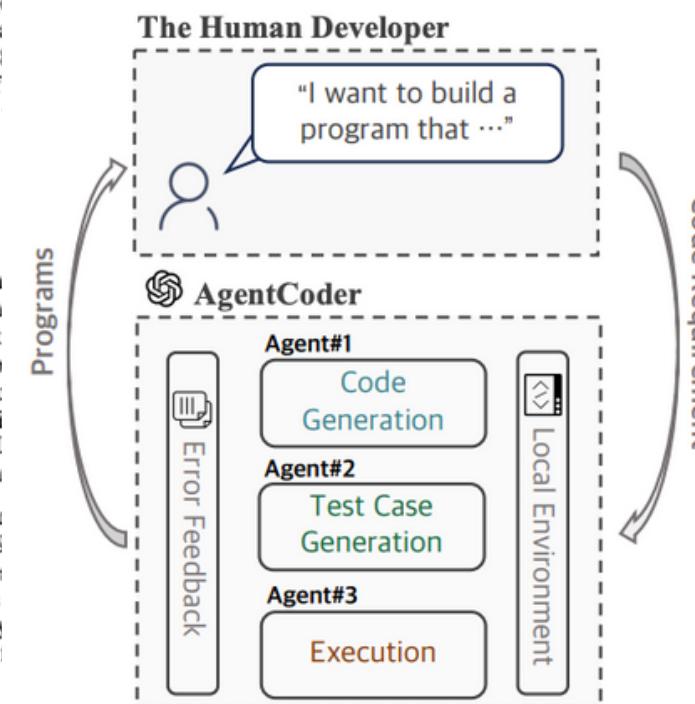
Advances in natural language processing (NLP) have been significantly boosted by the development of transformer-based large language models (LLMs). These models have revolutionized NLP tasks, particularly in code generation, aiding developers in creating software with enhanced efficiency. Despite their advances, challenges remain in balancing code snippet generation with effective test cases. To address these issues, this paper introduces AgentCoder, a novel code generation solution comprising a multi-agent framework with a specialized test designer agent in addition to the programmer agent and the test executor agent. During the coding procedure, the test designer agent generates effective test cases for the generated code, and the test executor agent runs the code with the test cases and writes feedback to the programmer agent for it to refine the code. This collaborative system enhances code generation efficiency with less cost, outperforming both single-agent models and earlier multi-ag

our extensive experiments on 14 LLMs and 16 b
ple, AgentCoder (GPT-4) achieves 96.3% and 91.
MBPP datasets with an overall token overhead of
of-the-art obtains only 90.2% and 78.9% pass@1
of 138.2K and 206.5K.

1 Introduction

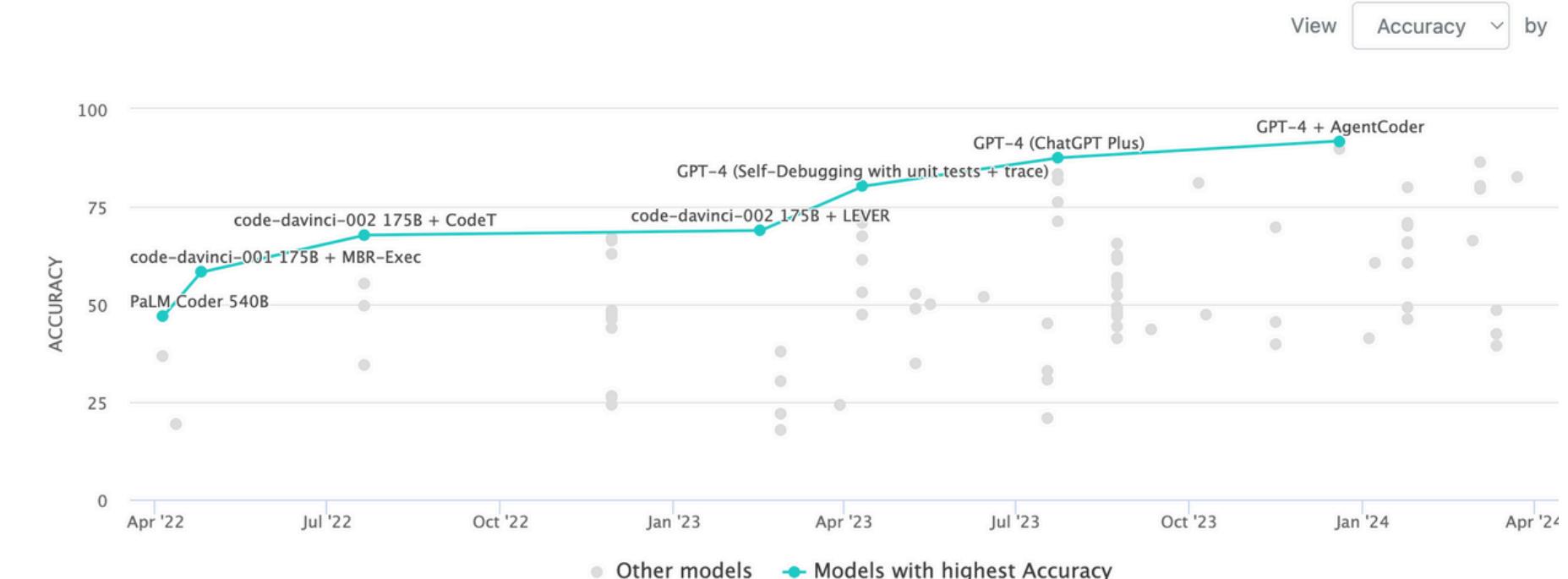
In recent years, natural language processing (NLP) has been revolutionized by transformer-based large language models (LLMs). These models, such as GPT-4 [4, 29] developed by OpenAI, have consistently set new records across a wide array of standard NLP tasks. One of the most promising applications of LLMs is in code generation for downstream tasks, where they play a vital role in automating software development [13, 34, 36, 28, 27, 24]. Through extensive pretraining on large amounts of publicly available data on GitHub, these code generation models have learned to generate code snippets that can be effectively applied to diverse code-related tasks. Numerous recent efforts have been made to improve the performance of LLMs in code generation, including in-context learning and its variations [11, 37, 20, 18, 42, 9], self-editing [3, 25, 26], and path-based self-refinement within the same context [27, 24]. A notable approach proposed by GPT-4 is Self-Edit to enhance the performance of LLMs in code generation. This method involves running the generated code against test cases that are manually provided, allowing the LLMs to refine the code based on the error messages of the test cases.

Preprint. Under review.



Code Generation on MBPP

Leaderboard Dataset



Rank	Model	Accuracy↑	Paper	Code	Result	Year
1	GPT-4 + AgentCoder	91.8	AgentCoder: Multi-Agent-based Code Generation with Iterative Testing and Optimisation			2023
2	GPT-3.5 Turbo (ChatGPT)	89.9	AgentCoder: Multi-Agent-based Code Generation with Iterative Testing and Optimisation			2023
3	GPT-4 (ChatGPT Plus)	87.5	How Does Naming Affect LLMs on Code Analysis Tasks?			2023
4	Claude 3 Opus	86.4	The Claude 3 Model Family: Opus, Sonnet, Haiku			2024

AgentCoder: Multi-Agent Code Generation with Iterative Testing and Self-optimisation

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Abstract

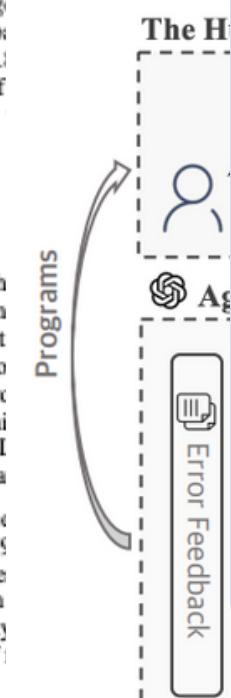
Advances in natural language processing (NLP) have been significantly driven by the development of transformer-based large language models (LLMs). These models have revolutionized NLP tasks, particularly in code generation, a critical component in creating software with enhanced efficiency. Despite their remarkable performance, challenges remain in balancing code snippet generation with effective testing and optimization. To address these issues, this paper introduces AgentCoder, a novel code generation solution comprising a multi-agent framework with a specialized test executor agent in addition to the programmer agent and the test executor agent. During the coding procedure, the test designer agent generates effective test cases for the generated code, and the test executor agent runs the code with the test cases and provides feedback to the programmer agent for it to refine the code. This iterative system enhances code generation efficiency with less cost, outperforming both single-agent models and earlier multi-agent systems. Our extensive experiments on 14 LLMs and 16 benchmarks, including the MBPP datasets with an overall token overhead of 1.5%, show that AgentCoder obtains only 90.2% and 78.9% pass@1 of 138.2K and 206.5K.

1 Introduction

In recent years, natural language processing (NLP) has been revolutionized by transformer-based large language models (LLMs). These models, such as GPT-4 and its variants, have consistently set new records in a wide array of standard NLP tasks. One of the most promising applications of LLMs is in code generation for downstream tasks, where they play a vital role in generating code snippets for various domains [13, 34, 36, 28, 27, 24]. Through extensive pretraining on large amounts of publicly available data on GitHub, these code generation models have shown great promise in solving complex problems.

Numerous recent efforts have been made to improve the performance of LLMs in code generation and its variations [11, 37, 20, 18, 42, 9]. A common approach is single-agent self-refinement within the same context, such as proposed Self-Edit to enhance the performance of LLMs in code generation [20]. Another approach is to run the generated code against test cases that are manually provided or automatically generated. This allows the LLMs to refine the code based on the error messages of the test cases.

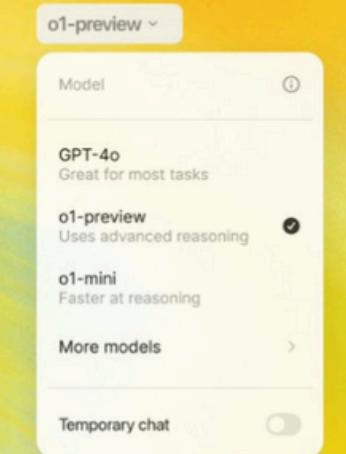
Preprint. Under review.



 OpenAI 
@OpenAI
X

We're releasing a preview of OpenAI o1—a new series of AI models designed to spend more time thinking before they respond.

These models can reason through complex tasks and solve harder problems than previous models in science, coding, and math.



o1-preview

Model

- GPT-4o Great for most tasks
- o1-preview** Uses advanced reasoning
- o1-mini Faster at reasoning
- More models >

Temporary chat

View Accuracy by

The H

openai.com

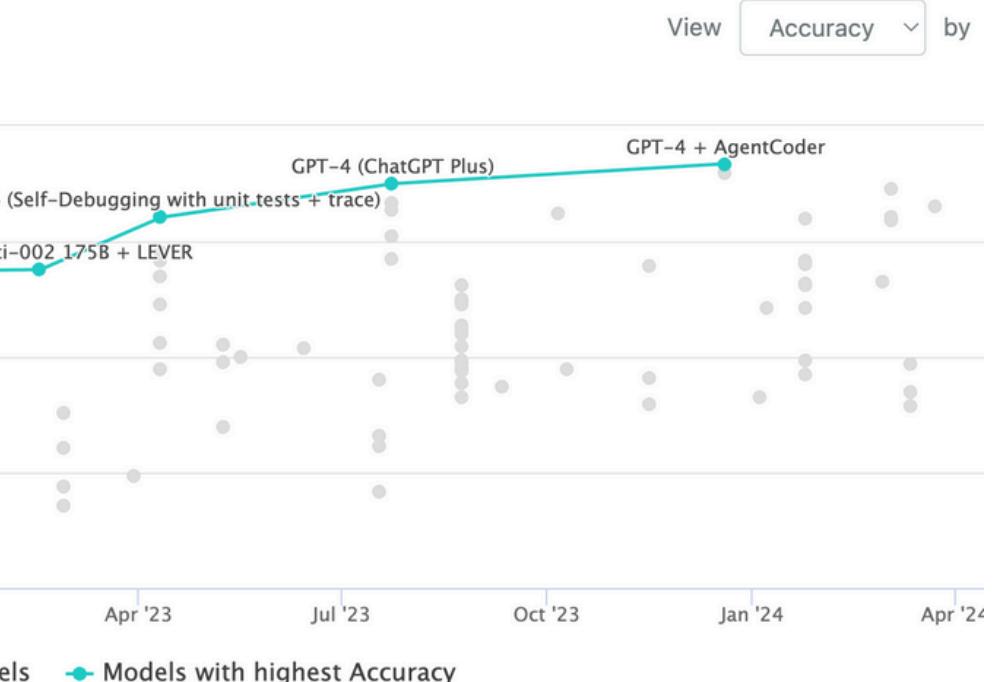
Introducing OpenAI o1

Introducing OpenAI o1

7:09 PM · Sep 12, 2024

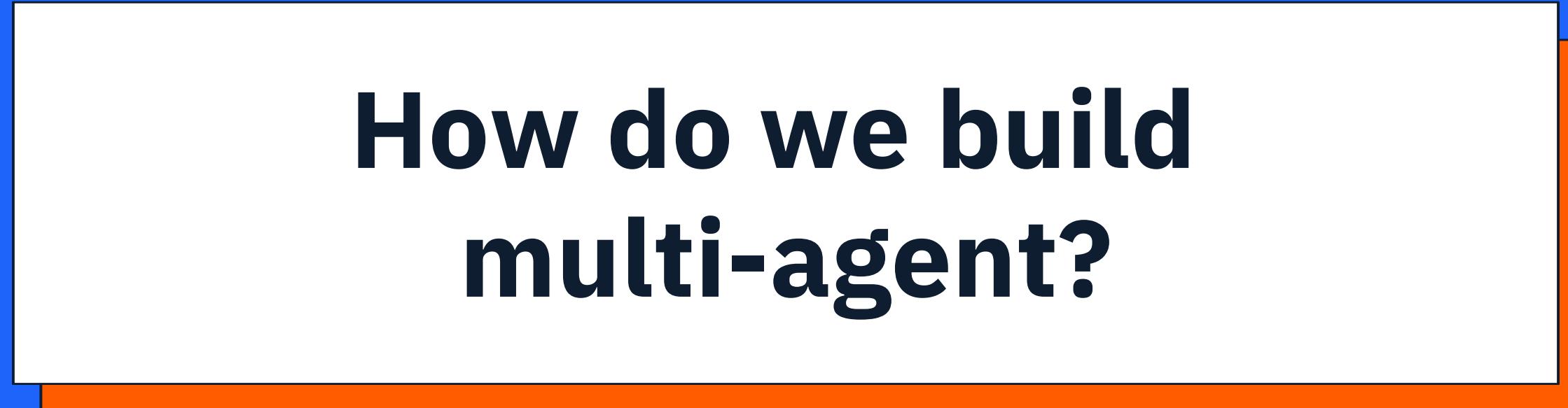
Execution

Unit



Code	Result	Year
AgentCoder: Multi-Agent-based Code Generation with Iterative Testing and Optimisation		2023
AgentCoder: Multi-Agent-based Code Generation with Iterative Testing and Optimisation		2023
How Does Naming Affect LLMs on Code Analysis Tasks?		2023
The Claude 3 Model Family: Opus, Sonnet, Haiku		2024





**How do we build
multi-agent?**



AutoGen

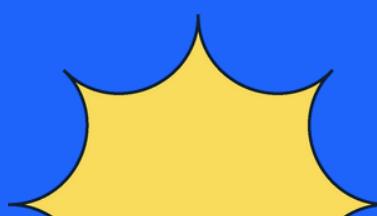
“

*AutoGen is an **open-source** framework that allows developers to build LLM applications via **multiple agents** that can **converse** with each other to accomplish tasks.*

”
arXiv:2308.08155v2 [cs.AI] 3 Oct 2023

Key features

- Conversation patterns for complex workflows
- Standard GenAI pipelines components (agents, models, tools)



AutoGen: Enabling Next-Gen LLM Applications via Multi-Agent Conversation

Qingyun Wu[†], Gagan Bansal^{*}, Jieyu Zhang[‡], Yiran Wu[†], Beibin Li^{*}

Erkang Zhu^{*}, Li Jiang^{*}, Xiaoyun Zhang^{*}, Shaokun Zhang[†], Jiale Liu[†]

Ahmed Awadallah^{*}, Ryen W. White^{*}, Doug Burger^{*}, Chi Wang^{*1}

^{*}Microsoft Research, [†]Pennsylvania State University

[‡]University of Washington, [†]Xidian University

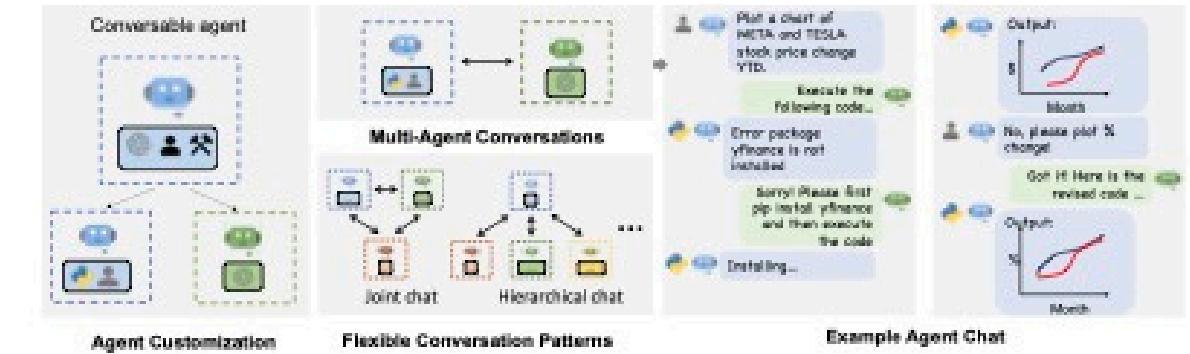


Figure 1: AutoGen enables diverse LLM-based applications using multi-agent conversations. (Left) AutoGen agents are conversable, customizable, and can be based on LLMs, tools, humans, or even a combination of them. (Top-middle) Agents can converse to solve tasks. (Right) They can form a chat, potentially with humans in the loop. (Bottom-middle) The framework supports flexible conversation patterns.

Abstract

AutoGen² is an open-source framework that allows developers to build LLM applications via multiple *agents* that can converse with each other to accomplish tasks. AutoGen agents are customizable, conversable, and can operate in various modes that employ combinations of LLMs, human inputs, and tools. Using AutoGen, developers can also flexibly define agent interaction behaviors. Both natural language and computer code can be used to program flexible conversation patterns for different applications. AutoGen serves as a generic framework for building diverse applications of various complexities and LLM capacities. Empirical studies demonstrate the effectiveness of the framework in many example applications, with domains ranging from mathematics, coding, question answering, operations research, online decision-making, entertainment, etc.

¹Corresponding author. Email: auto-gen@outlook.com

²<https://github.com/microsoft/autogen>



Workflow

Select or create an agent workflow.

General Agent Workflow

Create new workflows [here](#)

Sessions

Create a new session or select an existing session to view chat.

ada9e3bf-4079-4f66-8c8e-6a3 ...
just now

delete publish

45d4da7e-f9aa-4609-a408-984 ...
28 minutes ago

delete publish

680d8f0c-3e8f-4bb2-8c06-b54 ...
19 hours ago

delete publish

+ New

USER

create a 4 page pdf brochure on coffee from different parts of the world with some description of origins. E.g Ethiopian coffee may be in a glass on a table with a lush green forest in the background.

AGENT

The PDF brochure titled "Coffee_Brochure.pdf" has been successfully created. It includes images and descriptions of coffee from Ethiopia, Colombia, Brazil, and Vietnam, assembled into a 4-page document. Your brochure on coffee from different parts of the world is now ready. TERMINATE

Agent Messages (10 messages) | 2 mins 39 secs

Results (8 files)

Coffee_Brochure.pdf



77d9370c-1fe1-4658-a79a-ab789
0c93a6b.png



f7a649b1-ce4a-4d5f-91a3-0085b
2f574b6.png



a24eea2a-8d7c-4855-a1a8-953b
08b0bf41.png



6d3319d6-8041-49e1-acb5-439f
084440c5.png



generate_more_images.py

create_pdf_brochure.py

generate_images.py

Blank slate? Try one of the example prompts below

Stock Price

Sine Wave

Markdown

Paint

< close sidebar

 Skills

Models (2)

 + New Model

...

 Models

Create model configurations that can be reused in your agents and workflows.

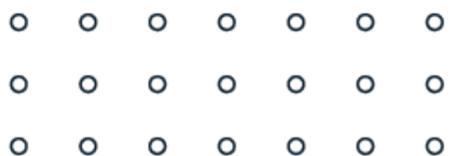
 Agents claude-3-5-sonnet-20 ...claude-3-5-sonnet-
20240620

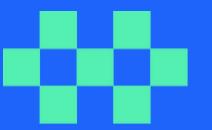
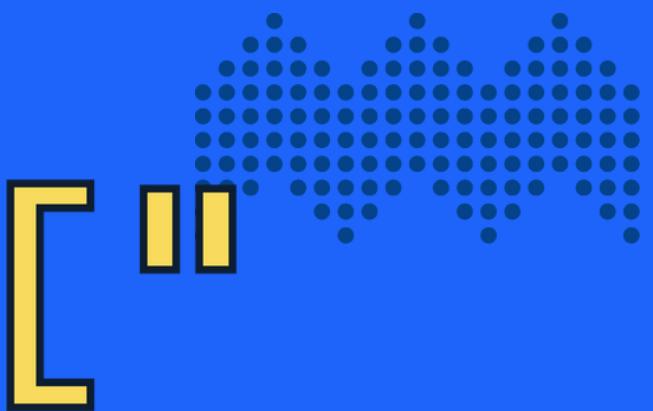
17 October 2024 at 17:11

 gpt-4o

gpt-4o

17 October 2024 at 17:11

 Workflows

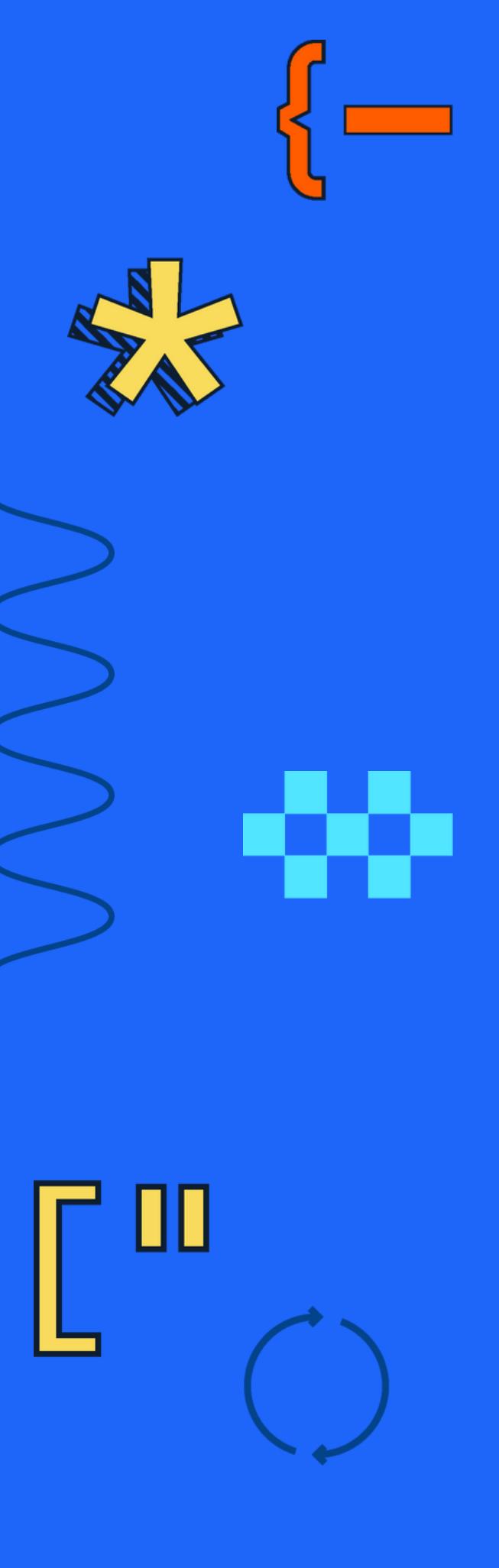


Live time!





Wrap up

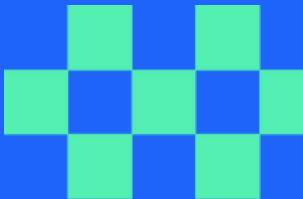


Advantages

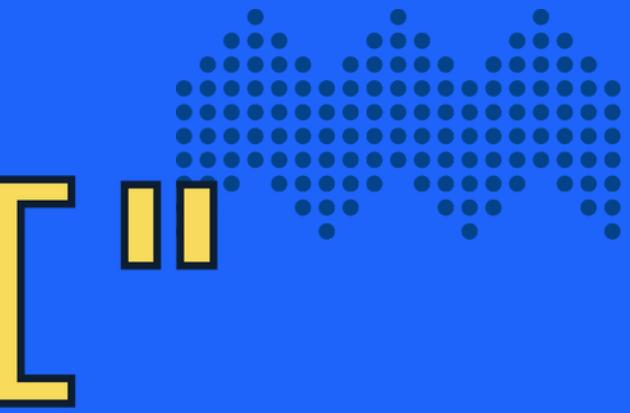
- **Sophisticated content generation** – creates highly detailed and nuanced outputs.
- **Iterative reasoning** – capable of refining solutions through multiple iterations.
- **External tool integration** – seamlessly integrates with external tools to expand functionality.
- **Multi-model support** – Can utilize multiple models to tackle different tasks.

Challenges

- **Time and cost** – longer processing times and higher resource demands.
- **Instability** – possible inconsistent performance, loops or unpredictable results.



Resources

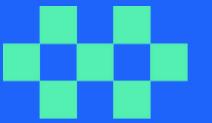
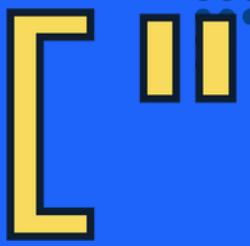


-  [**AutoGen: Enabling Next-Gen LLM Applications via Multi-Agent Conversation**](#)
-  [**AutoGen Studio: A No-Code Developer Tool for Building and Debugging Multi-Agent Systems**](#)
-  [**AgentCoder: Multi-Agent-based Code Generation with Iterative Testing and Optimisation**](#)
-  [**AutoGen framework docs**](#)
-  [**Code generation on MBPP benchmark**](#)
-  [**AutoGen GitHub repo**](#)
-  [**GenAI for Engineers Class by xtream**](#)
-  [**Create your own v0 – Codemotion Workshop Fest 2024 by xtream**](#)
-  [**Create your own v0 – repository**](#)





Let's get in touch!



Simone Colucci
Founder, Head of Product @
xtream



Riccardo Zoncada
Software Engineer @ xtream





{codemotion} CONFERENCE MILAN 2024

**Don't forget to
rate the talk!**



{codemotion} CONFERENCE MILAN 2024

Thanks!

