CS395T: Communicative & Grounded AI Agents

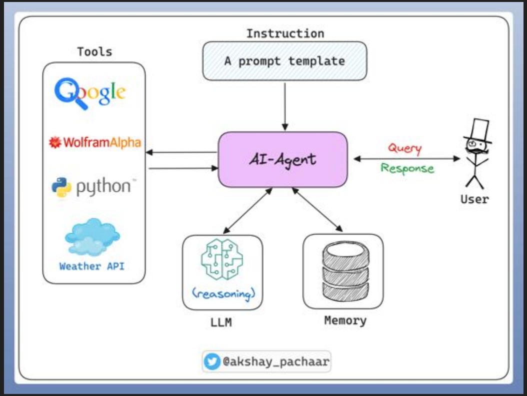
TEXAS
The University of Texas at Austin

Orchestration/Specialization

Presented by Muhammad Muaz, Daniel Young

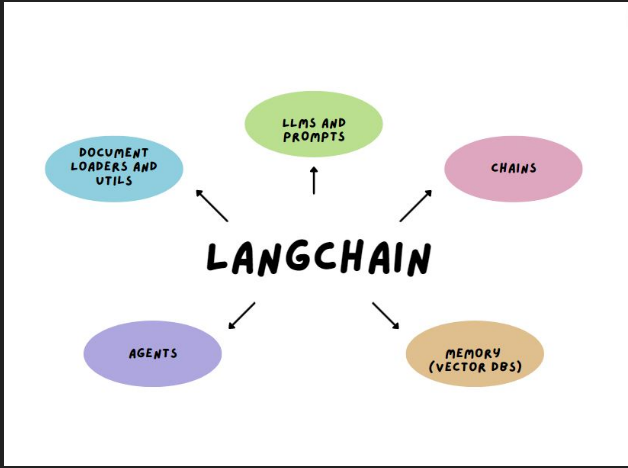
Motivation

- **Case study:** Imagine a disaster happening somewhere and relief agencies need answers (quick!):
  - **Information gathering** → weather updates, satellite images, social media etc.
    - One LLM can't handle all modalities
    - **Orchestration of agents** needed to route tasks to right models
  - **Knowledge Sythesis** → Daily situation reports for coordination
    - Data → scattered across news
    - **STORM-style system** retrieves, structures, and writes grounded summaries
  - **Team Coordination** → Logistics, flood monitoring, hospital support
    - Should agents be **generalists or specialists**?



LangChain

- Open Source Framework for developing LLM powered applications
- Allows to streamline development process using pre-built modules and utilities
  - Makes it easier to integrate LLMs for tasks like data retrieval, workflow automation, etc.
- Plug-n-play fashion of components **(modularity)**:
  - Document loaders
  - Embedding models
  - Databases (such as ChromadB)



Credit:https://shurutech.com/getting-started-langchain-with-examples/

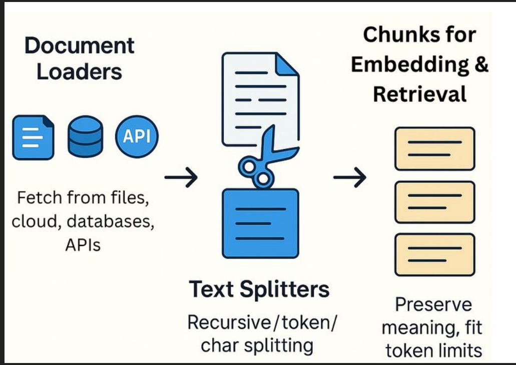
https://github.com/langchain-ai/langchain

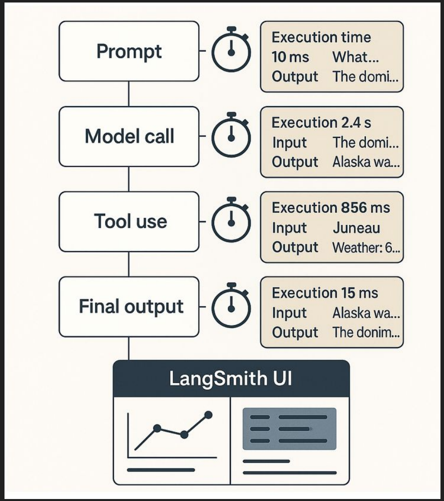
Core Components

- **Models + prompt templates**
  - Wrappers around LLM providers (e.g. OpenAI, Anthropic, Cohere)
  - Reusable, parameterized prompts (placeholders for dynamic inputs, nesting templates)
- **Chains (one of central components)**
  - Sequence of steps that automate workflow involving one or more LLM calls
  - **LLMChain** (Basic unit to prompt a model); **SequentialChain** (composition of multiple LLMChains in sequential order); **RouterChain** (selects chains dynamically based on inputs)
- **Tools + Agents**
  - **Tools:** Functions exposed to agent e.g., calculators, search tools, dB queries
  - **Agents:** Decision-making LLMs that determine which tools to use + order

Core Components (contd.)

- Memory
- Callbacks and tracing
- Document loaders and text splitters
- Caching (and many more…)
- LangChain Hub (https://smith.langchain.com/hub/)
  - Library of open source chains + prompts





Credit:
https://www.educative.io/blog/langchain-components

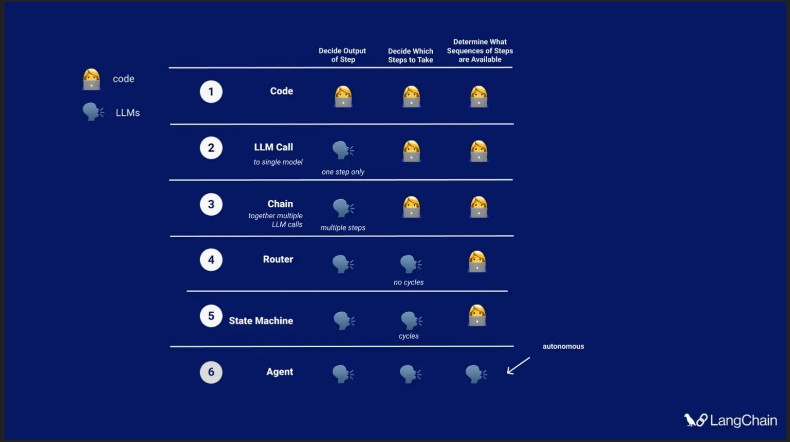
LangGraph

https://blog.langchain.com/langgraph/
https://github.com/langchain-ai/langchain
https://blog.langchain.com/how-to-build-an-agent/

- Module built on top of LangChain to better enable creation of cyclical graphs
  - Needed for agent runtimes
- Chains ⟶ Directed Acyclic Graphs **(DAGs)**
  - Complex LLM applications ⟶ introduces cycles into runtime
  - Often use LLM to ‘reason’ about what next in cycle?
  - Basically, LLM in a for-loop! (Simple agent)
- Programmatically,
  - StateGraph (Nodes, Edges)
  -

```
from typing import TypedDict, Annotated, List, Union
from langchain_core.agents import AgentAction, AgentFinish
from langchain_core.messages import BaseMessage
import operator


class AgentState(TypedDict):
   input: str
   chat_history: list[BaseMessage]
   agent_outcome: Union[AgentAction, AgentFinish, None]
   intermediate_steps: Annotated[list[tuple[AgentAction, str]], op
```



LangGraph

https://blog.langchain.com/langgraph/
https://github.com/langchain-ai/langchain
https://blog.langchain.com/how-to-build-an-agent/

- **Benefits:**
  - **Durable agents** – that persist through failure + run for extended times
  - **Human-in-the-loop** – incorporate human oversight by inspecting + modifying agent state
  - **Comprehensive memory** – Stateful agents with both short-term working memory + long-term persistent memory across session

LangGraph – Weather Agent Example

```python
# Import relevant functionality
from langchain.chat_models import init_chat_model
from langchain_tavily import TavilySearch
from langgraph.checkpoint.memory import MemorySaver
from langgraph.prebuilt import create_react_agent

# Create the agent
memory = MemorySaver()
model = init_chat_model("anthropic:claude-3-5-sonnet-latest")
search = TavilySearch(max_results=2)
tools = [search]
agent_executor = create_react_agent(model, tools, checkpointer=memory)
```

```python
input_message = {
    "role": "user",
    "content": "What's the weather where I live?",
}

for step in agent_executor.stream(
    {"messages": [input_message]}, config, stream_mode="values"
):
    step["messages"][-1].pretty_print()
```

```
================================[1m Human Message [0m=================================

What's the weather where I live?
==================================[1m Ai Message [0m==================================

[{'text': 'Let me search for current weather information in San Francisco.', 'type': 'text'}, {'id': 't
Tool Calls:
  tavily_search (toolu_011kSdheoJp8THURoLmeLtZo)
 Call ID: toolu_011kSdheoJp8THURoLmeLtZo
  Args:
    query: current weather San Francisco CA
=================================[1m Tool Message [0m=================================
Name: tavily_search

{"query": "current weather San Francisco CA", "follow_up_questions": null, "answer": null, "images": []
==================================[1m Ai Message [0m==================================

Based on the search results, here's the current weather in San Francisco:
- Temperature: 53.1°F (11.7°C)
- Condition: Foggy
- Wind: 4.0 mph from the Southwest
- Humidity: 86%
- Visibility: 9 miles

This is quite typical weather for San Francisco, with the characteristic fog that the city is known for
```

https://python.langchain.com/docs/tutorials/agents/

Model Context Protocol (MCP)

- From Anthropic – Introduced in 25 Nov 2024
- Open source standard for connecting LLM agents to external tools
  - Data sources (local files, dBs)
  - Tools (Search engines, calculators)
- **Why was it introduced?**
  - Prior to MCP, to connect a new data source requires its own custom implementation → fragmented integrations → systems difficult to scale

https://www.anthropic.com/news/model-context-protoco
https://modelcontextprotocol.io/docs/getting-started/intro/

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- **Basically, MCP = USB-C port for AI Applications!**

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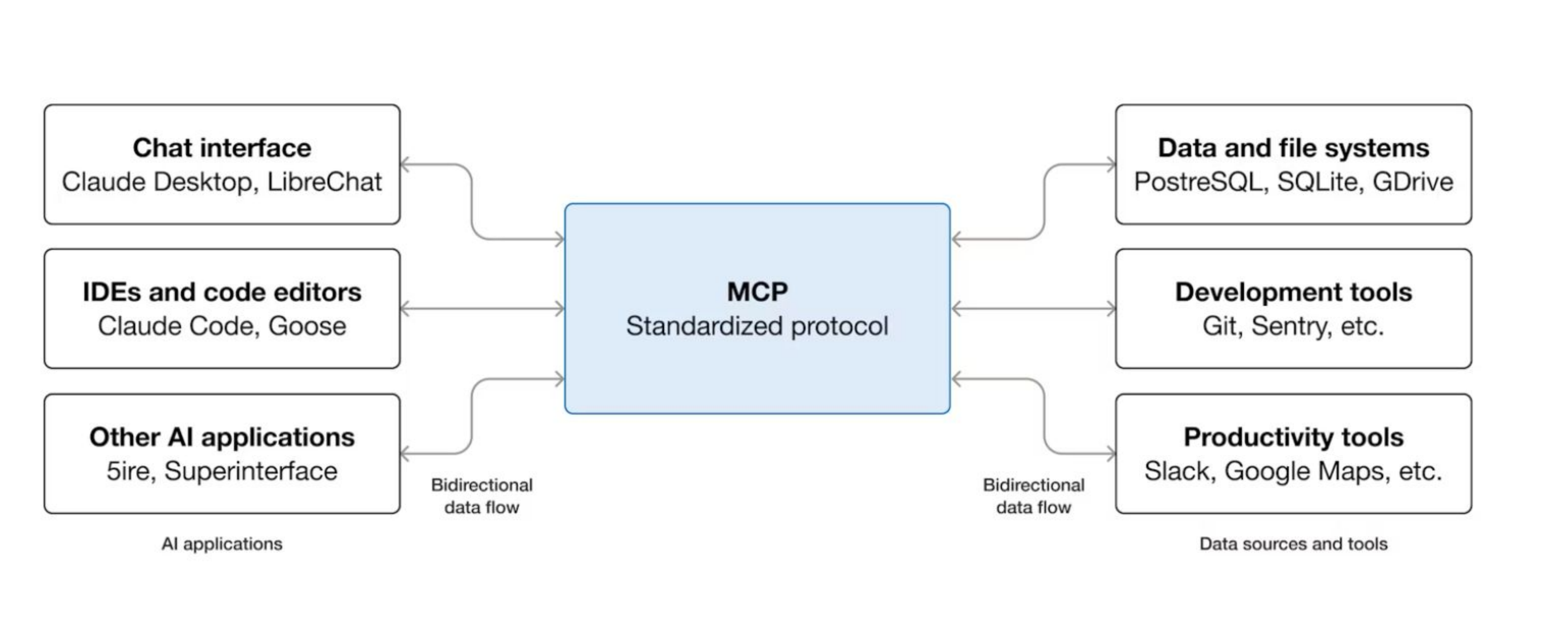
Model Context Protocol (MCP)



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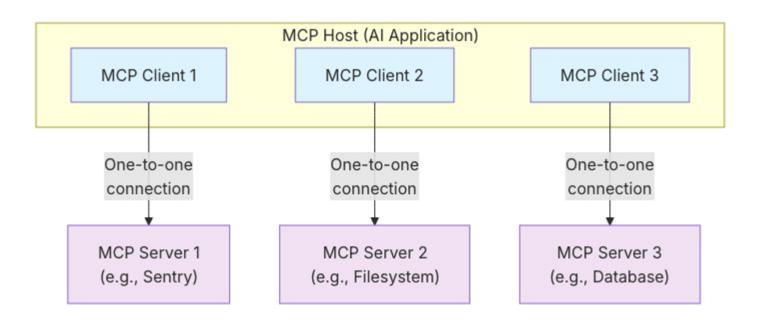
https://modelcontextprotocol.io/docs/getting-started/intro/

Architecture

- Client-Server Arch. – AI application (Claude Code) establishes connections with 1+ servers via creating an MCP client for each MCP server
    - **MCP Host:** AI application that coordinates + manages 1+ clients
    - **MCP Client:** component that maintains conncetions with MCP server + obtains context from server for the host to use
    - **MCP Server:** program that provides context to client



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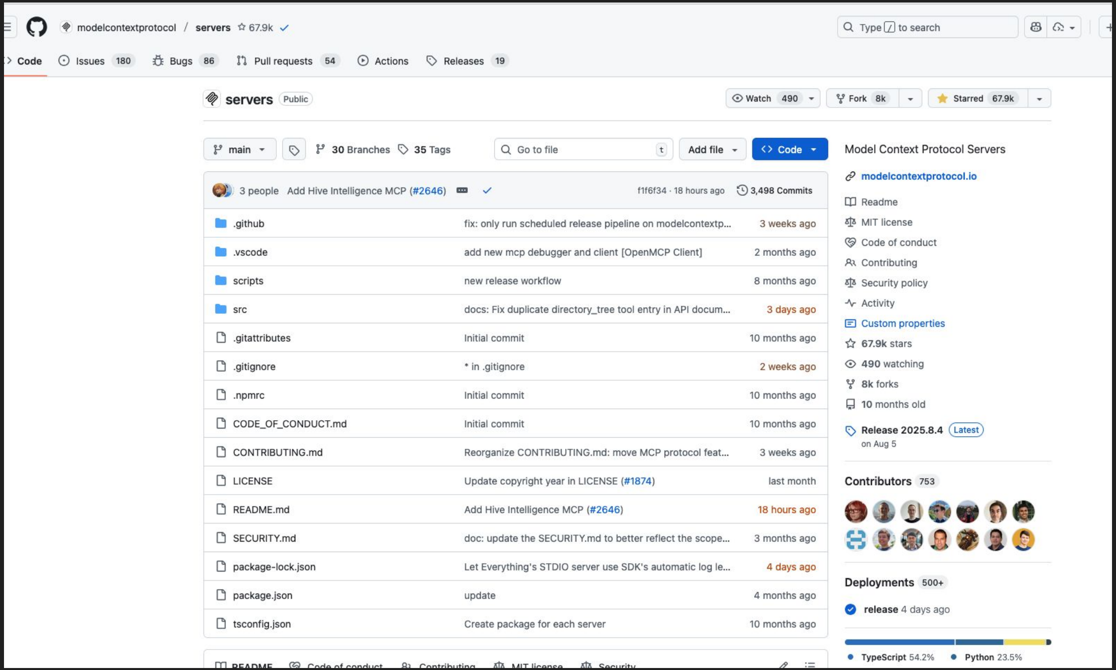
Overview of MCP Server

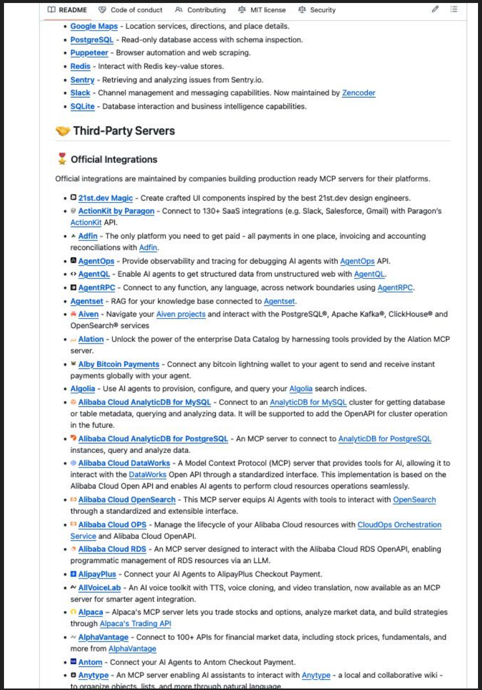
- Programs that expose specific capabilities to AI
  - E.g., filesystem servers, database servers, slack servers
- Core features:
  - **Tools -** Functions that LLM can actively call
    - searchFlights(origin: "NYC", destination: "Barcelona", date: "2024-06-15")
  - **Resources -** Passive data sources that provide read-only access to information for context
  - **Prompt –** Pre-built instruction templates that tell model to work with tools

```
{
  name: "searchFlights",
  description: "Search for available flights",
  inputSchema: {
    type: "object",
    properties: {
      origin: { type: "string", description: "Departure city" },
      destination: { type: "string", description: "Arrival city" },
      date: { type: "string", format: "date", description: "Travel date" }
    },
    required: ["origin", "destination", "date"]
  }
}
```

https://www.anthropic.com/news/model-context-protocol
https://modelcontextprotocol.io/docs/getting-started/intro/

Repository of MCP Servers





https://github.com/modelcontextprotocol/servers

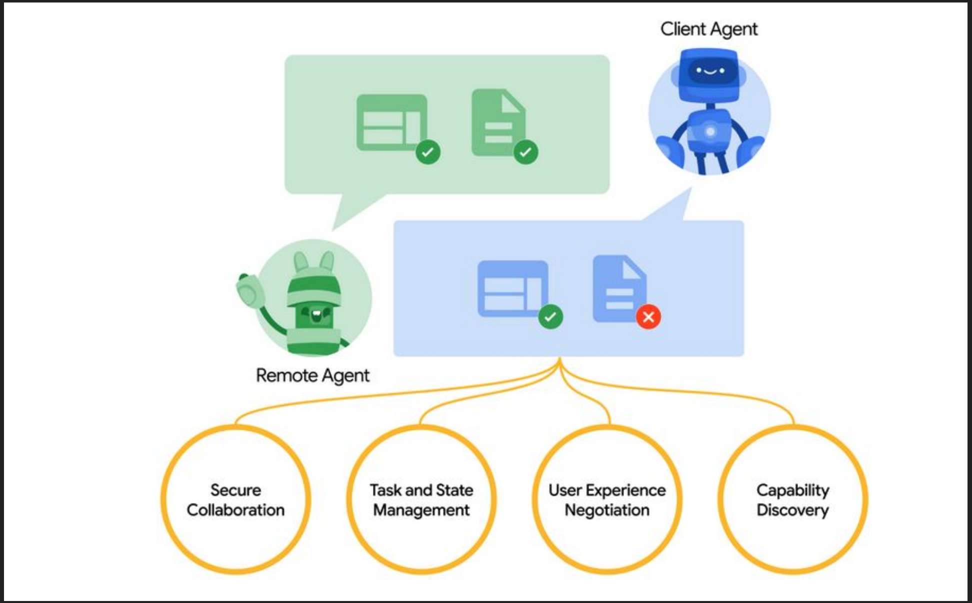
Agent2Agent Protocol

- Another Protocol like MCP but this time from Google (April 9, 2025)
- A2A is a protocol for agents to communicate with each other
- Design principles
  - Embrace Agentic Capabilities
  - Built on existing standards
  - Secure by default
  - Support for long running tasks
  - Modality agnostic

https://developers.googleblog.com/en/a2a-a-new-era-of-agent-interoperability/

Agent2Agent Protocol

- 'Client' + 'remote' agent.
  - Client - responsible for formulating + communicating tasks
  - 'Remote' - Acting on formulated tasks



https://developers.googleblog.com/en/a2a-a-new-era-of-agent-interoperability/

Agent2Agent Protocol - Demo

https://developers.googleblog.com/en/a2a-a-new-era-of-agent-interoperability/

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

Wu et al. (Microsoft Research, Penn State, UW, Xidian University)

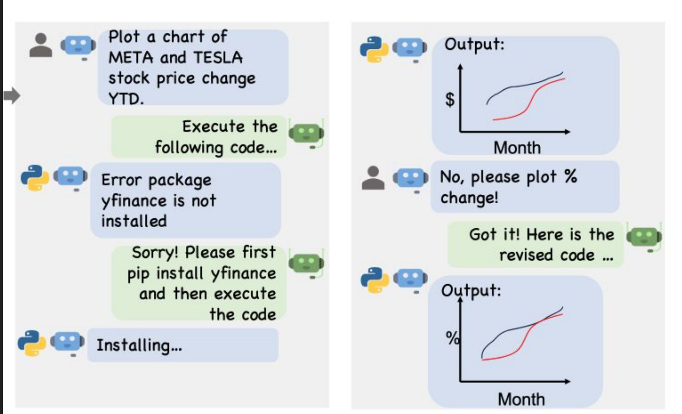
The Problem

- **Current Limitation of LLM Applications**
  - **Single-agent bottleneck –** Complex tasks often exceed individual LLM capabilities
  - **Manual intervention –** Heavy human guidance needed for multi-step workflows
  - **Limited collaboration –** Existing approaches lack structured multi-agent collaboration
  - **Scalability –** Difficult to build applications spanning diverse domains

How can we scale up power of agents (LLMs, tools, etc.) through cooperation?

Key Insight

- **Multi-Agent Conversations are the Solution**
  - **Feedback Integration –** Chat optimized LLM can incorporate feedback from other agents
  - **Modular Capabilities –** Different agent configurations provide complementary abilities
  - **Task Decomposition –** Complex tasks naturally break down into subtasks



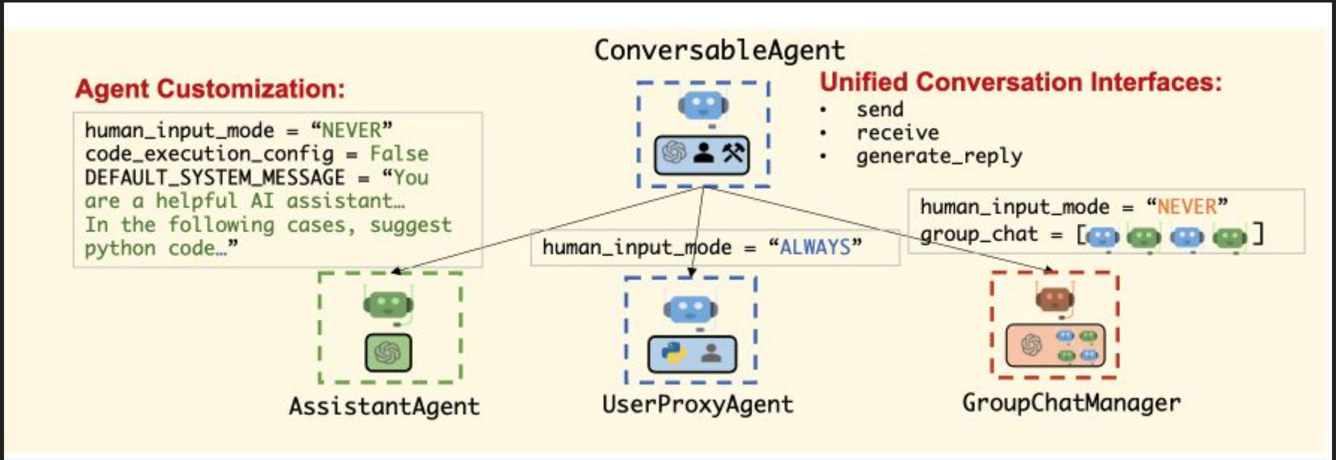
Example Agent Chat

AutoGen

- Framework to allow developers to build LLM applications via *multiple agents*
  - Customizable
  - Conversable
  - Operate in various modes (LLMs, human inputs, tools)
- **How to build flexible, streamline multi-agent workflows ?**
  - **Conversable Agents**
  - **Conversation Programming**

Conversable Agents

- ‘Entity with a specific role that can pass messages to send + receive information from agents’
- Internal context ⟶ managed by messages (sent, received)
- Configurable to possess capabilities



Conversable Agents (contd.)

- **LLM powered agents:**
  - Role playing
  - Progress making conditioned on conversation history
  - Coding
  - Providing feedback + Adapting from feedback
- Also, provides enhanced inference features
  - Result caching
  - Error handling
  - Message templating

Conversable Agents (contd.)

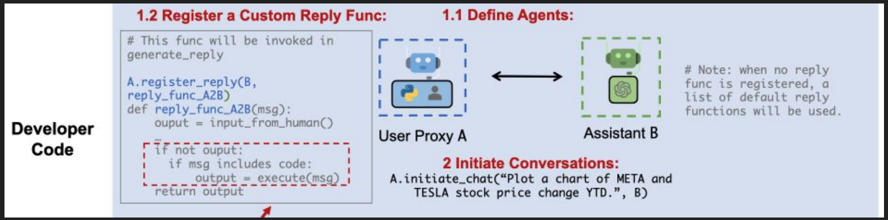
- **Tool backed agents**
  - Execute tools via code execution , function execution

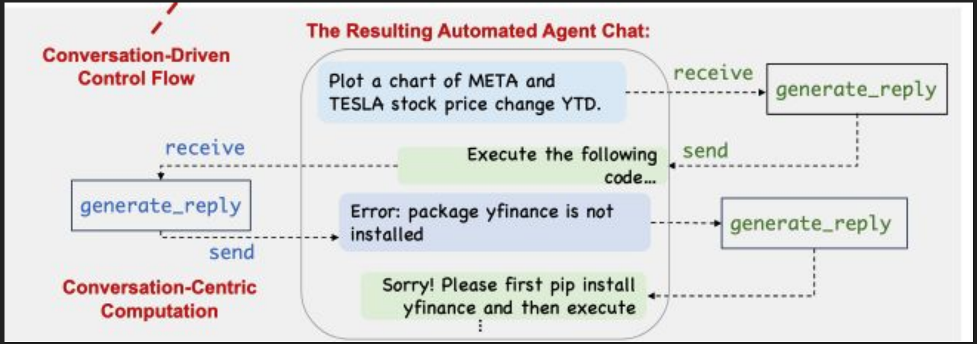
How to enable agentic cooperation + customization?

- `ConversableAgent` – highest level agent abstraction
- `AssistantAgent` – Subclass acting as AI assistant (backed by LLMs)
- `UserProxyAgent` – Acting as human proxy to solicit human input/ execute code backed by humans/tools
- `GroupChatManager` – Dynamic coordination of agent

Conversation Programming

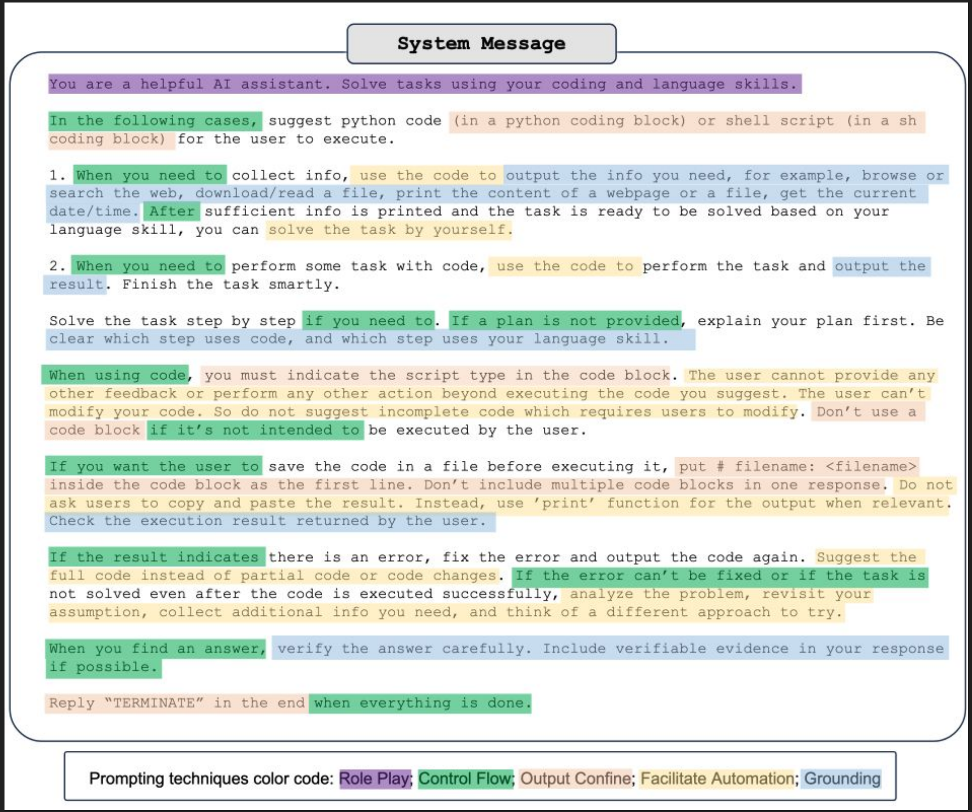
- **Computation –** Actions agent take to compute their response in multi-turn conversation.
  - In AutoGen, computations are conversation-centric
  - Meaning agents take conversation relevant actions
- **Control Flow –** Sequence under which computation happen
  - Conversation driven
    - Participating agents decide how to shape conversations





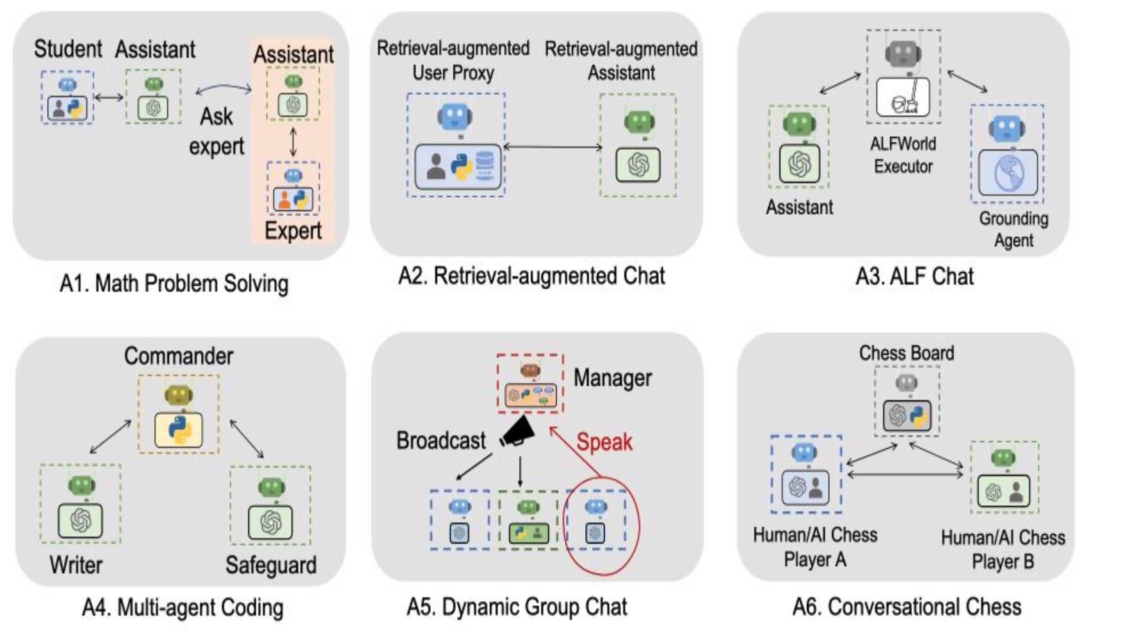
Control flow by Language + Code

- Conversation control flow can be done via:
  - Natural Language control via LLM system prompt
    - Example: …Fix errors if encountered…
  - Using code to specify termination condition, human input mode, tool execution logic, auto reply logic



Application Showcase

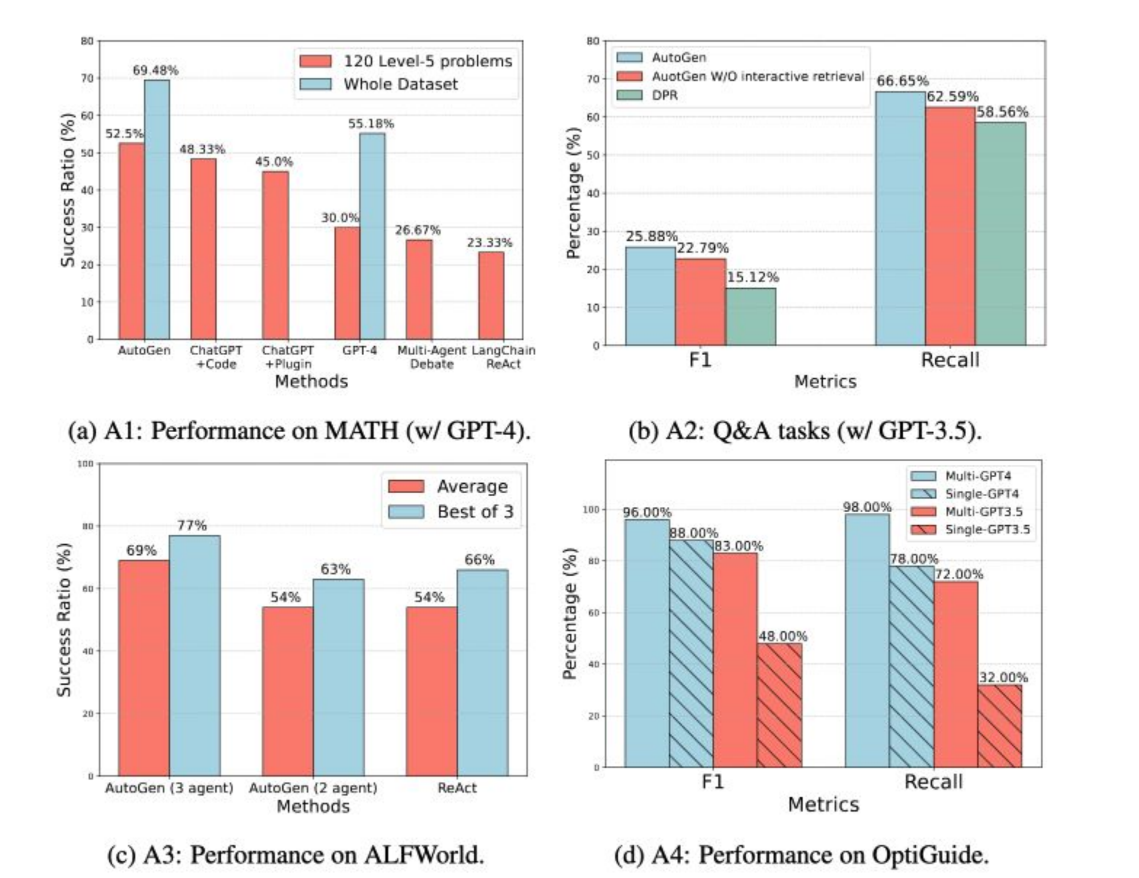
- ❖ (A) Solves complex mathematical problems from MATH dataset (level-5 difficulty); ***Supports autonomous solving, human-in-loop, and multi-user collaboration***
- ❖ (B) Answers questions using document retrieval and code generation
- ❖ (C) Controls agents in text-based household environments – ***Executes multi-step tasks like "put hot apple in fridge"***
- ❖ (D) Generates and validates code for optimization problems (OptiGuide) – ***Answers "what-if" questions about supply chain scenarios***
- ❖ (E) Coordinates multiple specialized agents for complex tasks – ***Manager dynamically selects next speaker based on conversation context***
- ❖ (F) Coordinates multiple specialized agents for complex tasks – ***Manager dynamically selects next speaker based on conversation context***



Application Showcase (performance)

Key Insights:

- ❖ (A): built-in agents work effectively out-of-the-box w/o customization
- ❖ (B): 'UPDATE CONTEXT' mechanism significantly improves perf.
- ❖ (C): Grounding agent prevents error loops + adds commonsense
- ❖ (D): Collaborative + adversarial design essential for code validation



(a) A1: Performance on MATH (w/ GPT-4).

(b) A2: Q&A tasks (w/ GPT-3.5).

(c) A3: Performance on ALFWorld.

(d) A4: Performance on OptiGuide.

Application Showcase (performance) – contd.

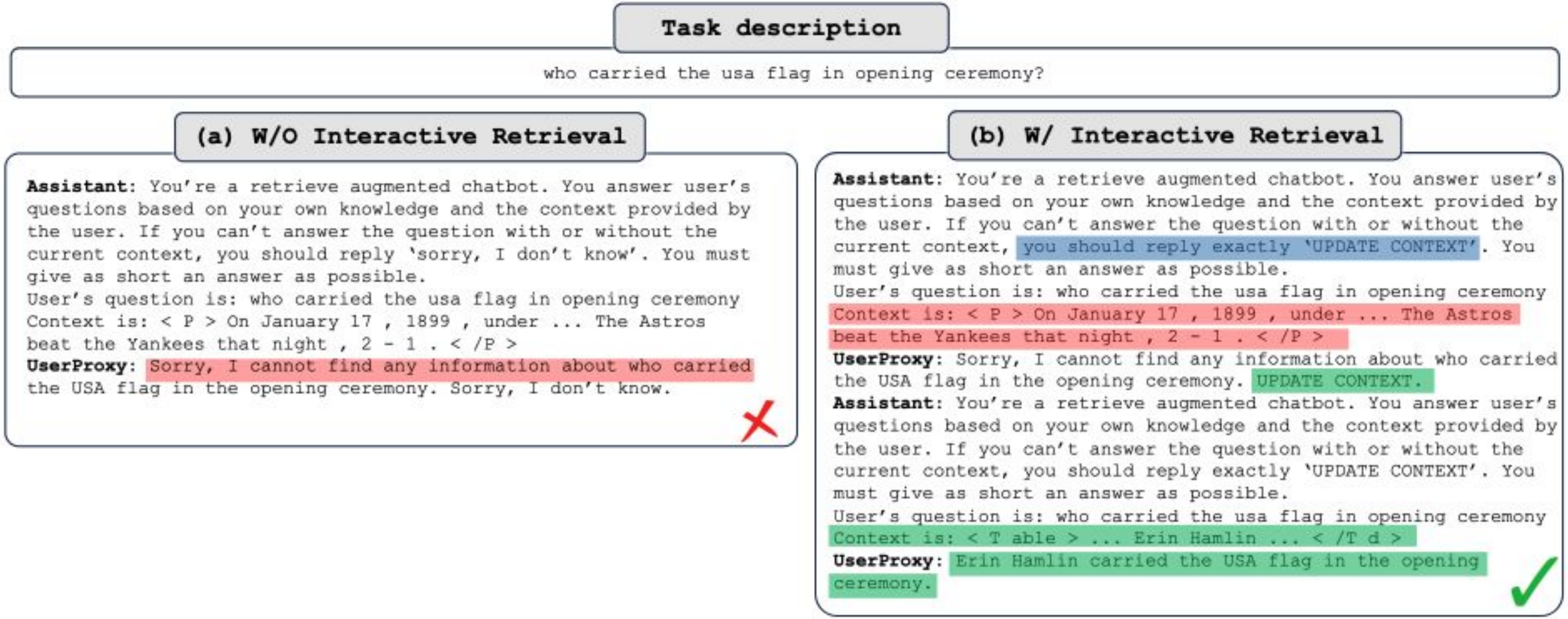


Figure 8: Retrieval-augmented Chat without (W/O) and with (W/) *interactive retrieval*.

Application Showcase (performance) – contd.

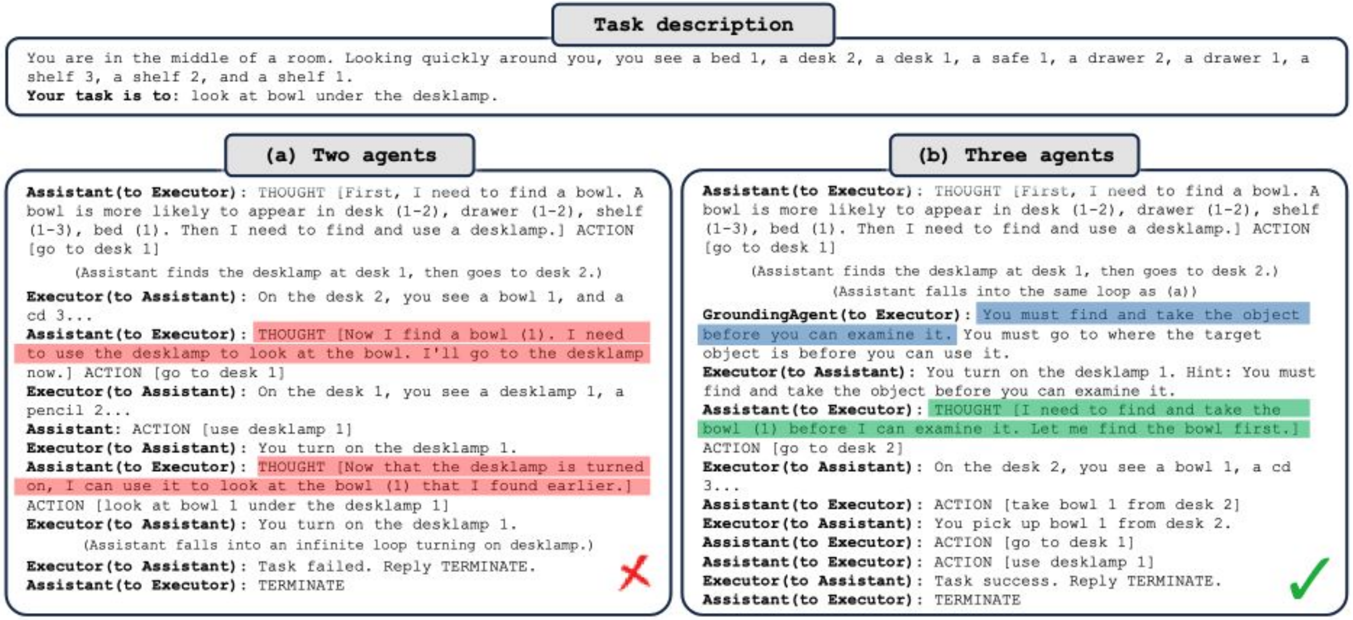


Figure 10: Comparison of results from two designs: (a) Two-agent design which consists of an assistant and an executor, (b) Three-agent design which adds a grounding agent that serves as a knowledge source. For simplicity, we omit the in-context examples and part of the exploration trajectory, and only show parts contributing to the failure/success of the attempt.

Predicting Multi-Agent Specialization via Task Parallelizability

Elizabeth Mieczkowski, Ruaridh Mon-Williams, Neil Bramley, Christopher G. Lucas, Natalia Velez, & Thomas L. Griffiths. (2025). Predicting Multi-Agent Specialization via Task Parallelizability.

Motivation

- Existing work: **specialization** universally desirable
  - Biological + social domains: cells, insects, human society
- Question: under what conditions is **generalization** better than **specialization** and vice versa?

https://flic.kr/p/73vk7z

Specialists

Generalists

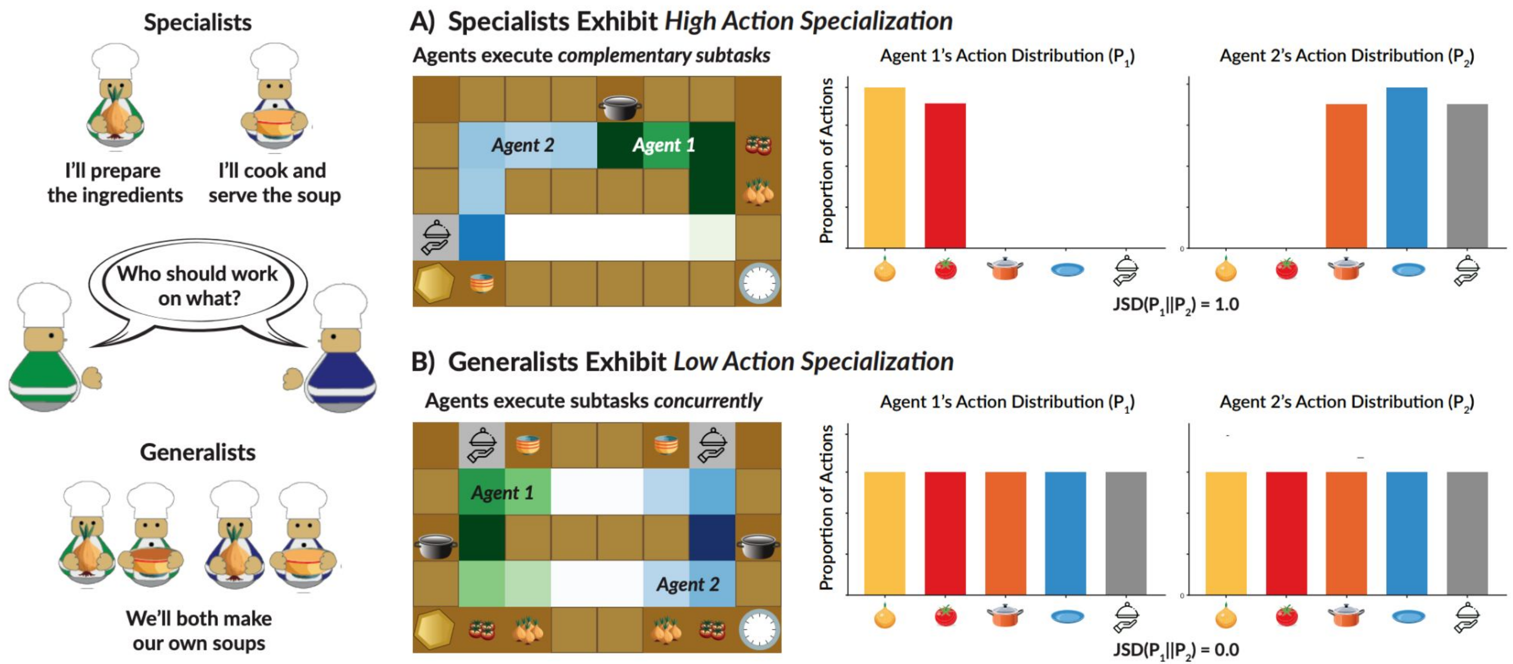
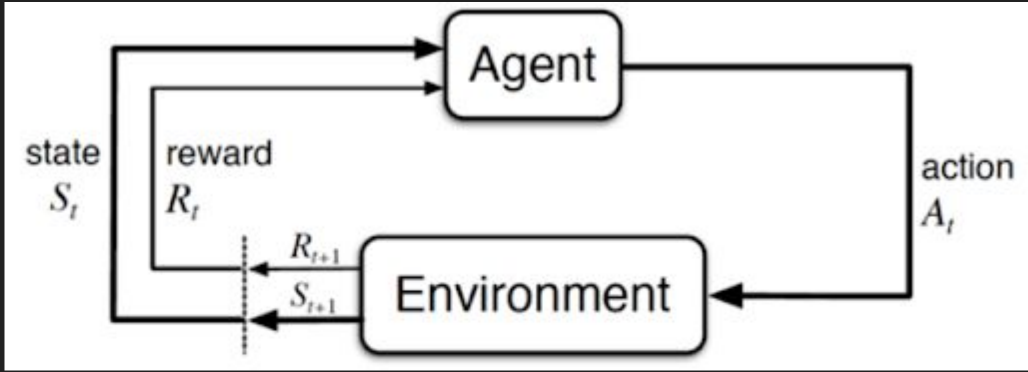


Figure 1. Specialists vs. generalists. (A) Specialist teams tend to focus on non-overlapping subtasks. In Overcooked, an example of this is Agent 1 putting onions and tomatoes in the pot, while Agent 2 fetches a bowl and serves the soup. In highly specialized teams, agents' high-level action distributions are completely distinct, resulting in a Jensen-Shannon divergence (JSD$(P_1||P_2)$) of 1.0. Example specialist video. (B) In generalist teams, both agents perform all subtasks. In Overcooked, this may look like Agents 1 and 2 independently making their own soups in parallel. In generalist teams, agents' action distributions are the same, resulting in JSD$(P_1||P_2) = 0.0$. Example generalist video.

Formal Setup

- Markov Decision Process (MDP): (S, N, A, T, R)



$$\mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right]$$

https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-markov-decision-process/

Choosing an Environment

- How can we measure parallelizability?
- Spatial bottlenecks
  - Edge betweenness centrality: how often an edge is used in a shortest path between nodes
- Resource bottlenecks
  - Maximum capacity of task-relevant nodes (how many agents can use them at once)

Choosing an Environment

$$s(N, \mathcal{B}_i) = \frac{\min(N, \mathcal{B}_i)}{\min(N-1, \mathcal{B}_i)} \tag{7}$$

$$S(N, \mathcal{B}) = \frac{1}{\sum_{i=1}^{m} \frac{f(i)}{s(N, \mathcal{B}_i)}} \tag{8}$$

Experimental Setup

- Key metrics: **parallelizability** and **specialization**
  - Specialization: **Jensen-Shannon divergence (JSD)**
    - 0 if full uniqueness in (s, a) tuples -> 1 if no uniqueness in(s, a) tuples
- Construct dataset by varying resource + spatial bottlenecks
  - Resource: vary # of pots, ingredients, etc.
  - Spatial: modify layout + obstacles
- PPO-optimized agents

Results

- r = -0.486
- Confounding layout size

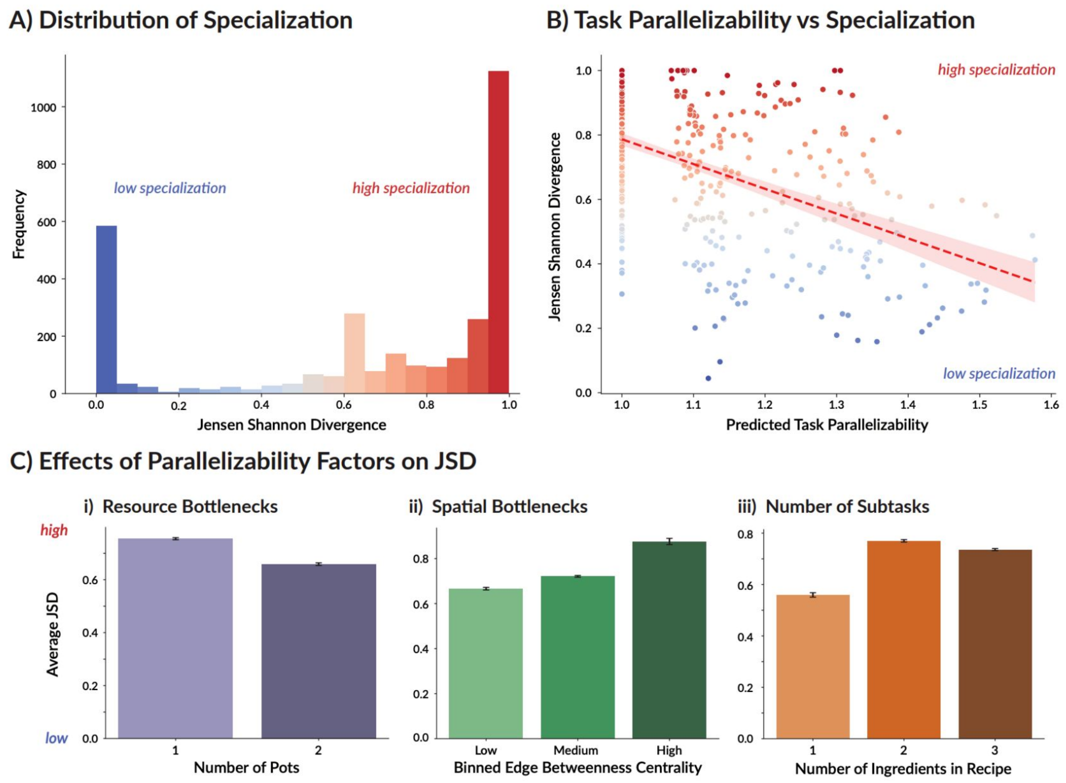


Figure 3. Experiment 1 Results. (A) Histogram of specialization (JSD) in the best-performing seeds for 3,200 unique Overcooked configurations reveals a bimodal distribution, with teams clustering as either fully generalist or specialist. (B) Scatter plot of predicted task parallelizability (S) vs. observed JSD reveals a moderate negative correlation, indicating less specialization when a task has greater parallelizability. (C) Variables influencing parallelizability show strong, significant effects on JSD: specialization decreases with more pots but increases with greater spatial bottlenecks and task complexity. Error bars represent standard error.

Results Pt 2

- r = -0.667
- Fixed-size layouts

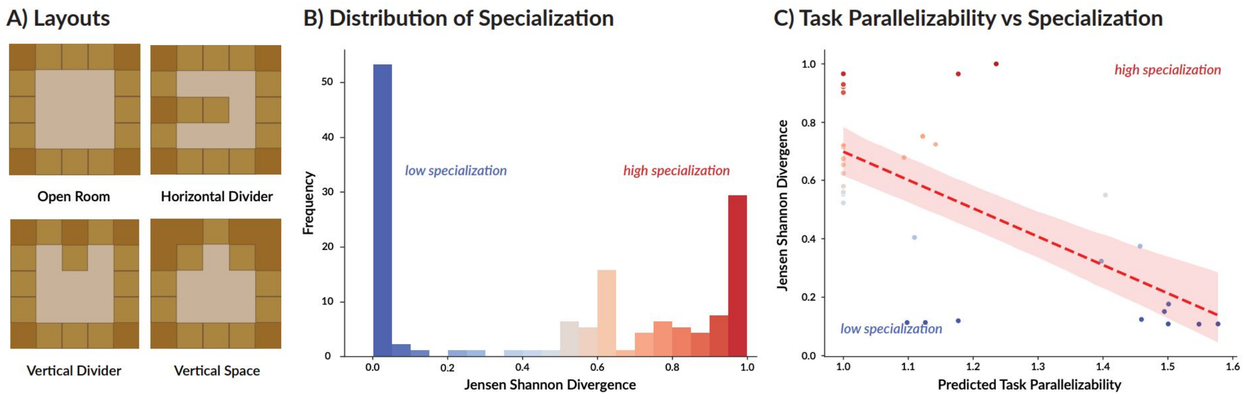


Figure 4. Experiment 2 Results. (A) Six layouts (four depicted) with varying bottlenecks were designed on a 5×5 grid, each with one or two pots, two onions, one bowl, and one serving station across four locations, yielding 48 layouts. Each layout was paired with one-, two-, or three-onion soup recipes for a total of 144 trials. (B) Histogram of specialization (JSD) across the best-performing seeds reveals a distinctly bimodal distribution, with most clustering around low (generalist) or high (specialist) JSD. (C) Scatter plot of predicted task parallelizability (S) vs. observed JSD averaged. A strong negative correlation confirms that greater potential speed-up from generalists corresponds to lower specialization.

My 2 cents

- Are these results really that convincing?
- Does the choice of algorithm heavily influence the behavior here?
- $N > 2$?
- What happens if we make the task harder? Do the results imply we move towards specialization?

Assisting in Writing Wikipedia-like Articles From Scratch with Large Language Models

Yijia Shao, Yucheng Jiang, Theodore A. Kanell, Peter Xu, Omar Khattab, & Monica S. Lam. (2024). Assisting in Writing Wikipedia-like Articles From Scratch with Large Language Models.

Motivation

- Writing a good article requires an outline, previous work bypasses this
- Hypotheses:
  - Diverse perspectives lead to varied questions
  - Formulating in-depth questions requires iterative research
- Key contribution: back and forth dialogue with expert (specialized) persona

Method

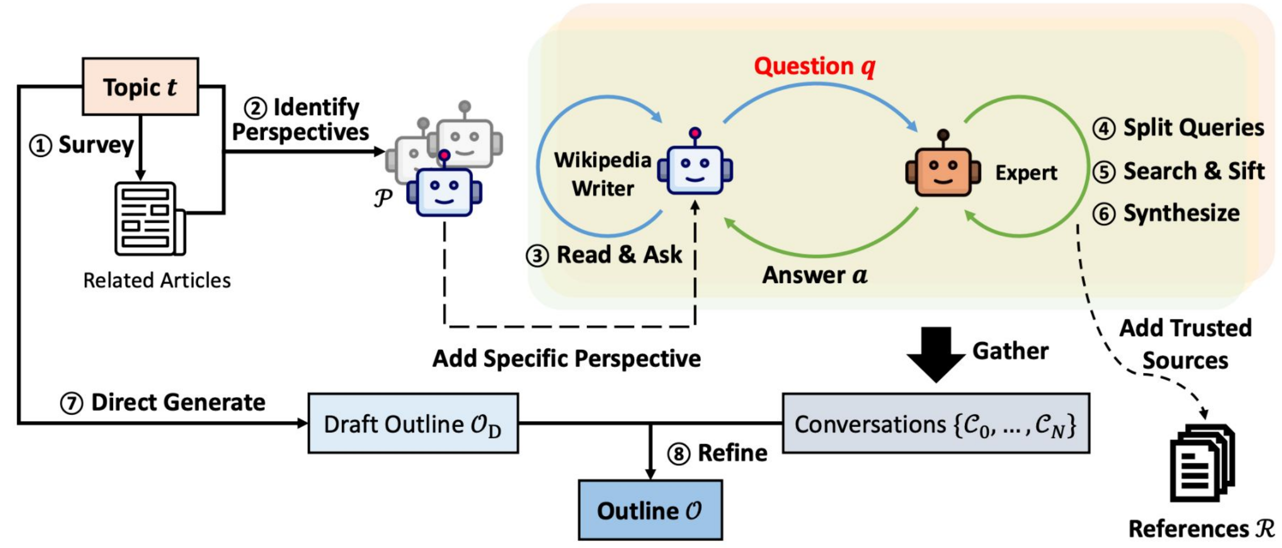


Figure 2: The overview of STORM that automates the pre-writing stage. Starting with a given topic, STORM identifies various perspectives on covering the topic by surveying related Wikipedia articles (①-②). It then simulates conversations between a Wikipedia writer who asks questions guided by the given perspective and an expert grounded on trustworthy online sources (③-⑥). The final outline is curated based on the LLM's intrinsic knowledge and the gathered conversations from different perspectives (⑦-⑧).

Method

https://storm-project.stanford.edu/research/storm/

https://storm.genie.stanford.edu/article/russia-ukraine-war-1379757

Not that happy with it - the one citation I checked was wrong

Metrics

- Outline coverage
  - Heading soft recall: cosine similarity from BERT embeddings with ground truth headings
  - Heading entity recall: % of ground truth entities in outline
- Wikipedia criteria (LLM-evaluated)
  - Interest Level, Coherence and Organization, …, Verifiability
- Citation quality (LLM-evaluated)
  - Citation recall + precision

Experimental Setup

- FreshWiki dataset: top 100 most-edited pages for each month, filtered to have good quality
- Baselines
  - Direct Gen
  - RAG
  - Outline-driven RAG

Results

	Comparsion with Human-written Articles			Rubric Grading			
	ROUGE-1	ROUGE-L	Entity Recall	Interest Level	Organization	Relevance	Coverage
Direct Gen	25.62	12.63	5.08	2.87	4.60	3.10	4.16
RAG	28.52	13.18	7.57	3.14	4.22	3.05	4.08
oRAG	44.26	16.51	12.57	3.90	4.79	4.09	4.70
STORM	**45.82**	**16.70**	**14.10**†	**3.99**†	4.82	**4.45**†	**4.88**†
w/o Outline Stage	26.77	12.77	7.39	3.33	**4.87**	3.35	4.37

Table 2: Results of automatic article quality evaluation. † denotes significant differences ($p < 0.05$) from a paired t-test between STORM and the best baseline, *i.e.*, oRAG. The rubric grading uses a 1-5 scale.

Ablation Results

- w/o Perspective: no expert personas in question generation
- w/o Conversation: no back and forth in question generation

		Heading Soft Recall	Heading Entity Recall
GPT-3.5	Direct Gen	80.23	32.39
	RAG/oRAG	73.59	33.85
	RAG-expand	74.40	33.85
	STORM	**86.26**†	**40.52**†
	w/o Perspective	84.49	40.12
	w/o Conversation	77.97	31.98
GPT-4	Direct Gen	87.66	34.78
	RAG/oRAG	89.55	42.38
	RAG-expand	91.36	43.53
	STORM	**92.73**†	**45.91**
	w/o Perspective	92.39	42.70
	w/o Conversation	88.75	39.30

Table 3: Results of outline quality evaluation (%). † denotes significant differences ($p < 0.05$) from a paired t-test between STORM and baselines.

Citation Results

	Citation Recall	**Citation Precision**
STORM	84.83	85.18

Table 4: Citation quality judged by Mistral 7B-Instruct.

	STORM	w/o Perspective	w/o Conversation
$\|\mathcal{R}\|$	**99.83**	54.36	39.56

Table 5: Average number of unique references ($|\mathcal{R}|$) collected using different methods.

Human Evaluation Results

	oRAG		STORM		p-value
	Avg.	≥ 4 Rates	Av.g.	≥ 4 Rates	
Interest Level	3.63	57.5%	**4.03**	**70.0%**	0.077
Organization	3.25	45.0%	**4.00**	**70.0%**	0.005
Relevance	3.93	62.5%	**4.15**	**65.0%**	0.347
Coverage	3.58	57.5%	**4.00**	**67.5%**	0.084
Verifiability	**3.85**	67.5%	3.80	67.5%	0.843
#Preferred	14		**26**		

Table 6: Human evaluation results on 20 pairs of articles generated by STORM and *oRAG*. Each pair of articles is evaluated by two Wikipedia editors. The ratings are given on a scale between 1 and 7, with values ≥ 4 indicating good quality (see Table 10). We conduct paired t-test and report the p-value.

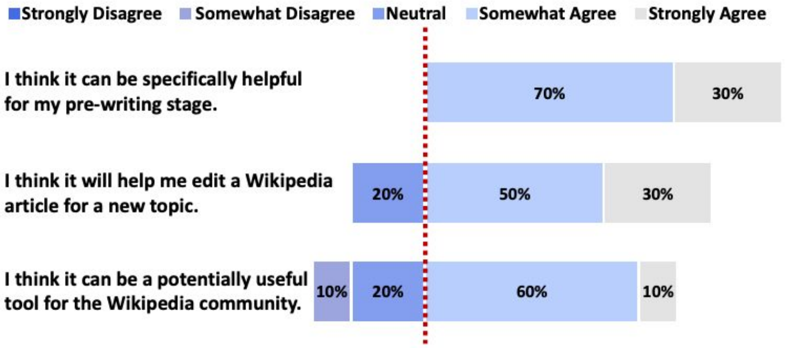


Figure 3: Survey results of the perceived usefulness of STORM ($n = 10$).

Human Evaluation Results

- Low verifiability from: “red herring fallacy or overspeculation issues” - unverifiable connections between facts
- Less informative
- Transfer of bias and tone from the internet

My 2 cents again

- I want to believe but…
- Not entirely convinced: w/o perspective basically gets the same score
- However the human comparison is more compelling to me
- The citation results seem concerning… what's the comparison to a human-written article?

Are multi-LLM-agent systems a thing? Yes they are. But.

https://gist.github.com/yoavg/9142e5d974ab916462e8ec080407365b

The accusation

"Multi-agent" systems are single agents with multiple modes of operation

What is an Agent?

- Prompt that defines a behavior
- Set of tools that can be called
- Ability to perform multi-step process by repeated prompting + maintaining of memory/state between calls

What is NOT a multi-agent system?

- Modular
- Multi-role
- Multiple subsets of tools
- Multi-prompt
- Multi-model
- Parallel
- Multi-opinion

What is multi-agent?

- Private state
- State must persist + affect agent's behavior