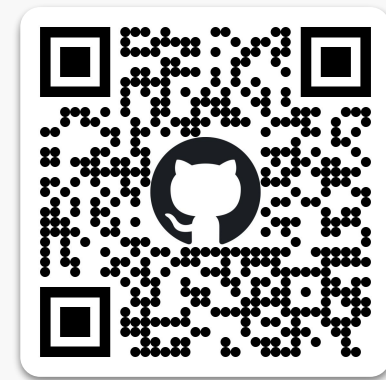


Building Scalable Agentic Systems for Science

*Concepts, Architectures, and Hands-On with **Academy***

Greg Pauloski, Alok Kamatar, Kyle Chard, Ian Foster

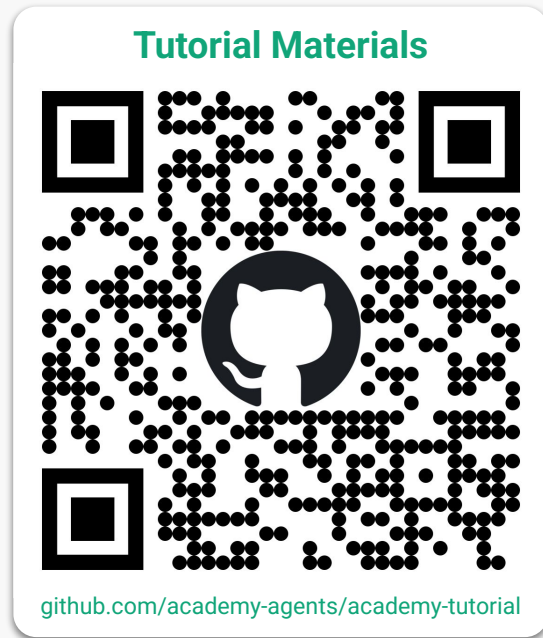


github.com/academy-agents/academy-tutorial

Welcome!

In this tutorial we will cover:

- Concepts and motivations behind agentic systems
- Architectures for scalable, distributed agentic workflows
- Overview of the Academy framework
- Patterns for integrating with scientific tools and infra
- Hands-on: build your own agents
- Discussion: challenges and future directions



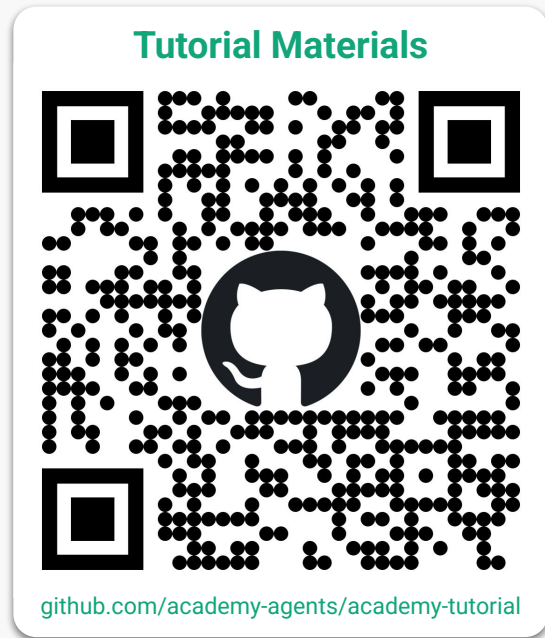
Welcome!

Audience

- Researchers and scientists exploring AI-driven or autonomous workflows
- Developers and engineers building tools for HPC and data-intensive systems
- Anyone interested in how agentic systems can scale and accelerate discovery

Requirements

- Familiarity with Python (+1 for asyncio experience)
- MacOS/Linux/WSL with Python 3.10–3.13



Agenda

Time	Topic
8:30 - 9:00	Introduction
9:00 - 9:30	Academy Overview
9:30 - 10:00	Hands-on: Getting Started
10:00 - 10:30	Break
10:30 - 10:45	Agentic Workflows for Science
10:45 - 11:30	Hands-on: Battleship
11:30 - 11:45	Demo: Academy MCP
11:45 - 12:00	Wrap up

Room 126



Greg Pauloski
NVIDIA (prev: UChicago)



Alok Kamatar
UChicago



Kyle Chard
UChicago & ANL



Ian Foster
UChicago & ANL

Introduction

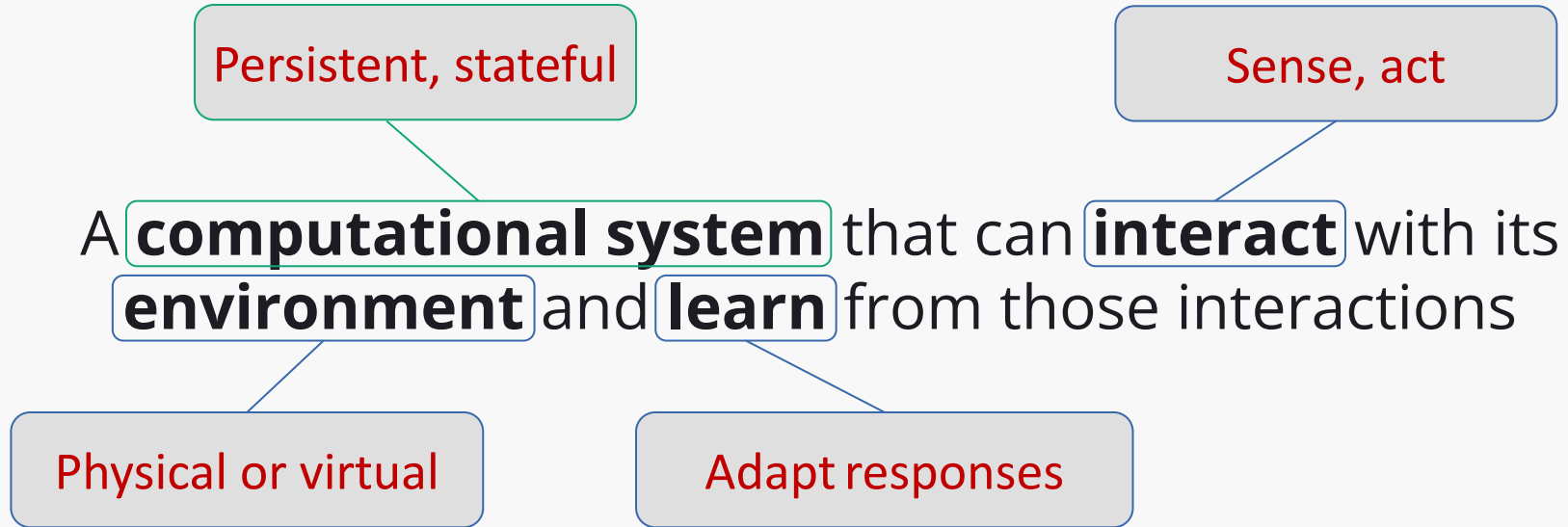
8:30 – 9:00 am

What is an “agent”?

- In **computer software**, a “software agent” is [Wikipedia] **“a computer program that acts for a user or another program in a relationship of agency”**
- In **artificial intelligence (AI)**, an “intelligent agent” is [also Wikipedia] **“an entity that perceives its environment, takes actions autonomously to achieve goals, and may improve its performance through machine learning or by acquiring knowledge”**
 - An AI component, sensors, actuators, memory

See also: <https://gist.github.com/simonw/beaa5f90133b30724c5cc1c4008d0654>

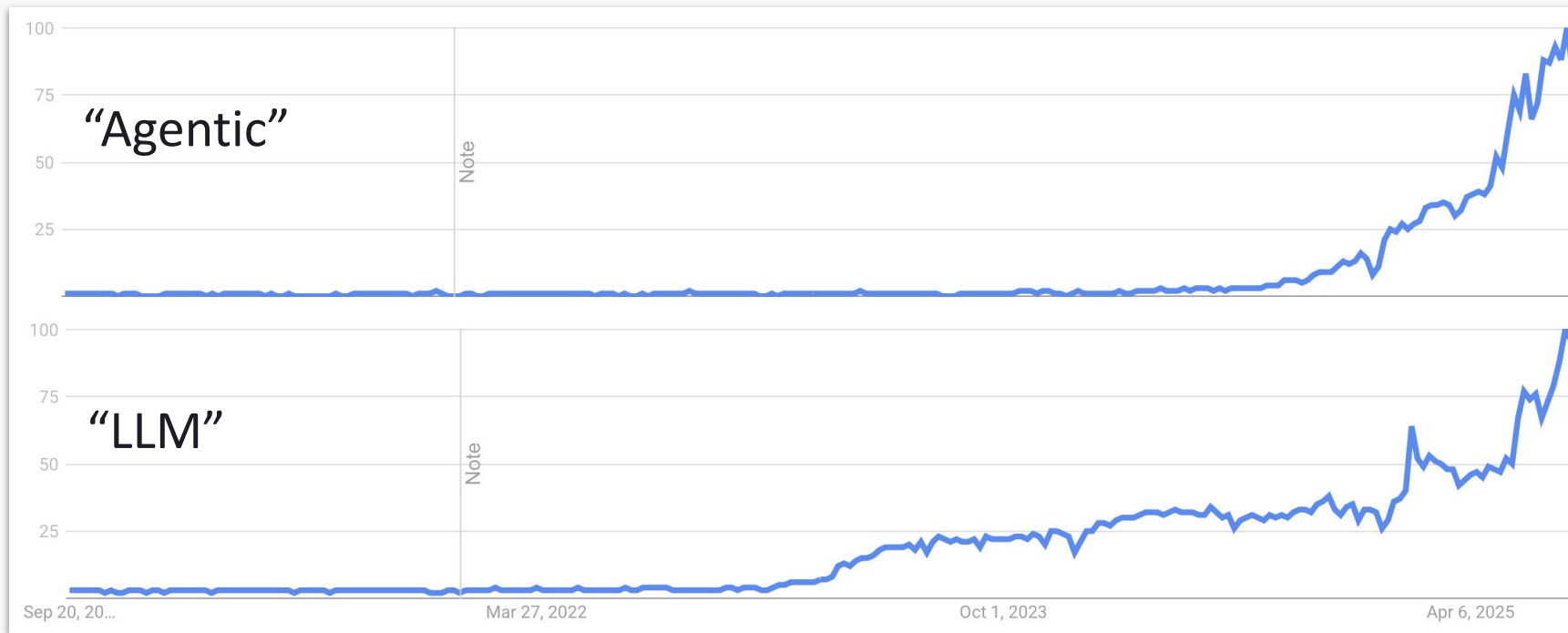
Related concept: An “embodied agent”



The “sense-plan-act-learn” loop

- Initialize state and goals
- Repeat until termination:
 - **Sense:** Gather observations from environment
 - **Plan:** Evaluate goals and state, plan/select next action
 - **Act:** Execute chosen action on environment
 - **Learn:** Update internal state, memory, or model based on outcomes

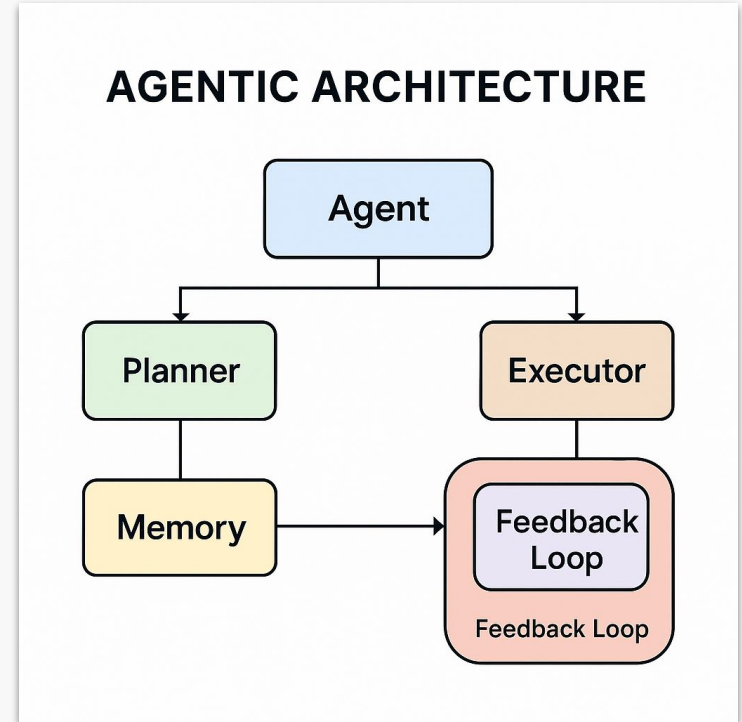
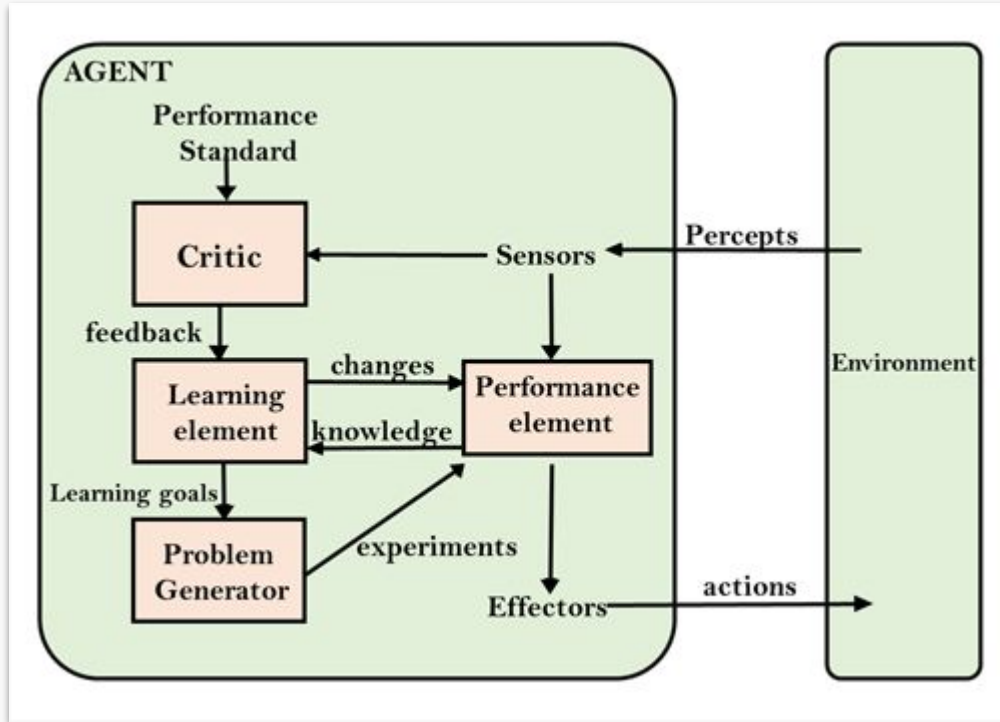
Current excitement around agents is due to LLMs



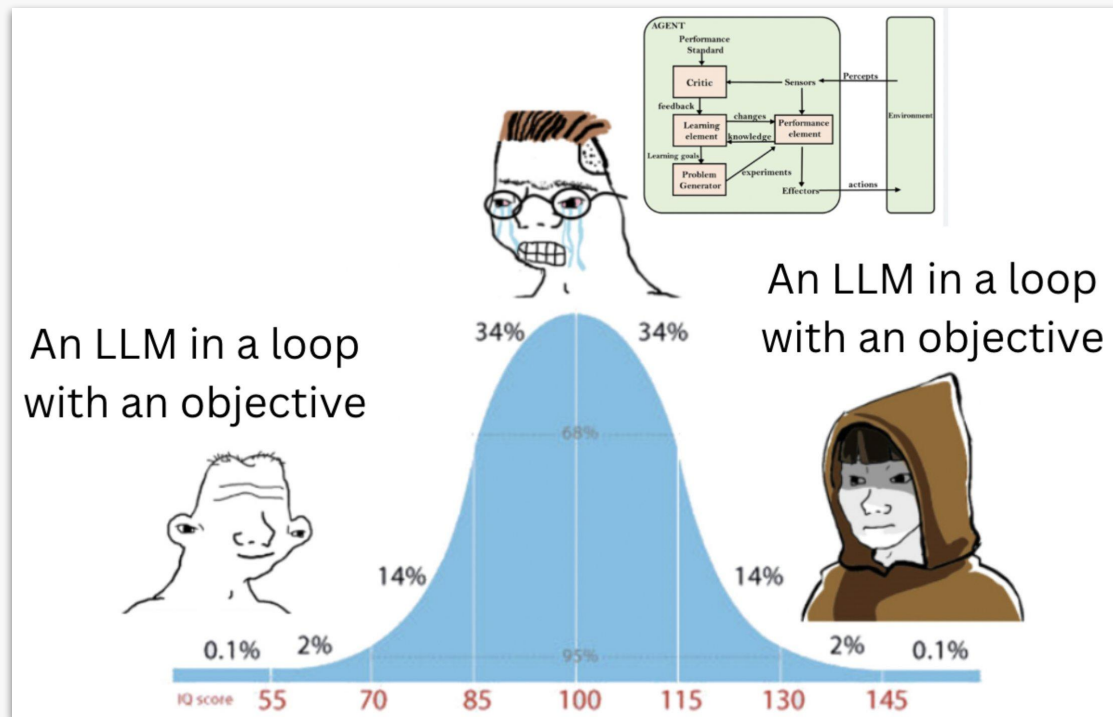
<https://trends.google.com>



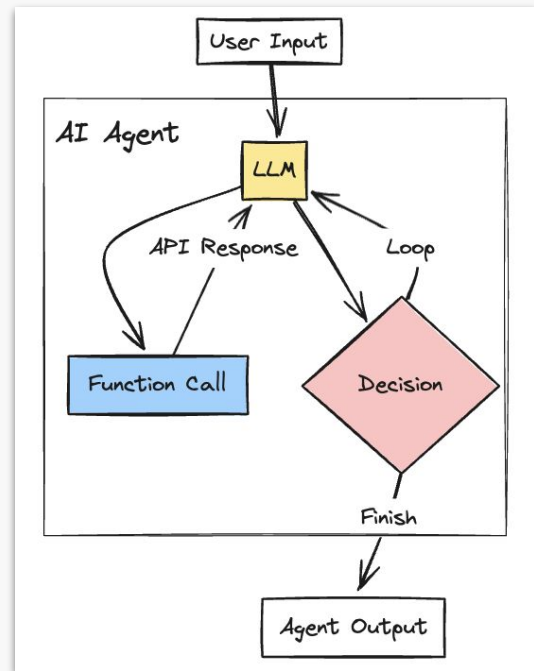
Many related ideas regarding agentic architecture



A simple perspective



https://x.com/josh_bickett/status/1725556267014595032



@SullyOmarr

“CACTUS: Chemistry Agent Connecting Tool Usage to Science”

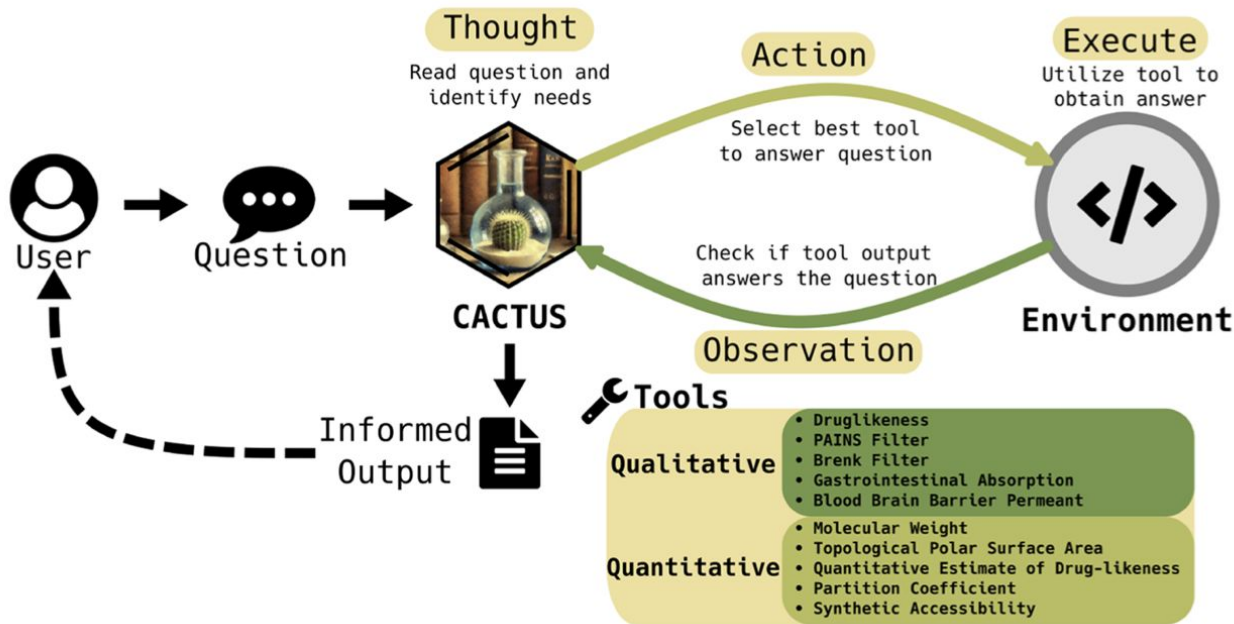


Figure 1. General workflow of the CACTUS agent that details how the LLM interprets input to arrive at the correct tool to use to obtain an answer. Starting from the user input, CACTUS follows a standard “Chain-of-thought” reasoning method with a Planning, Action, Execution, and Observation phase to obtain an informed output.

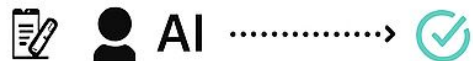
<https://pubs.acs.org/doi/pdf/10.1021/acsomega.4c08408>

Overview

- What is an “agent”?
- **LLMs, foundation models, reasoning models**
- Agents and scientific discovery



Traditional ML



AI> ✓



AI> ✓



AI> ✓



AI> ✓

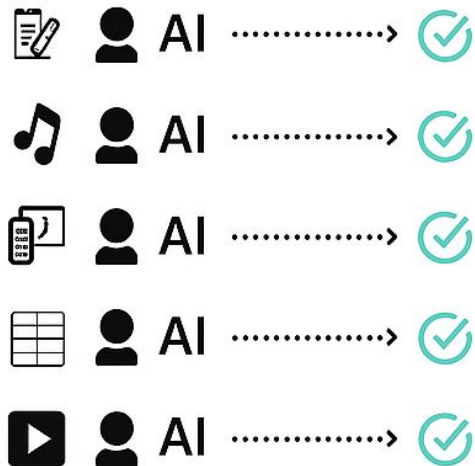


AI> ✓

- Individual siloed models
- Require task-specific training
- Lots of human supervised training



Traditional ML

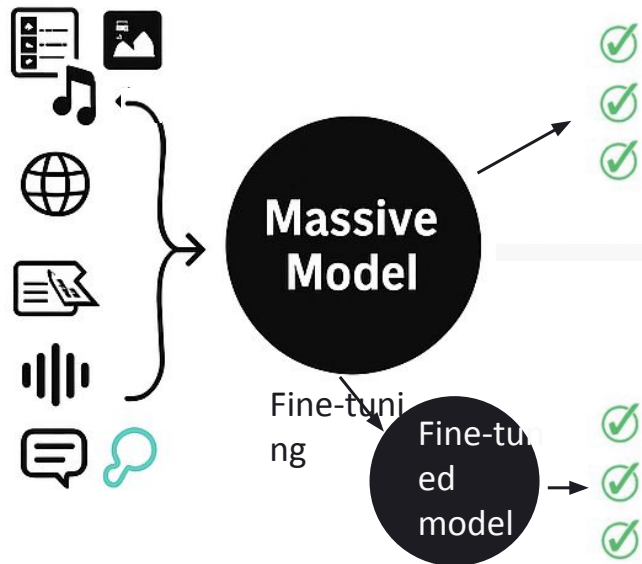


- Individual siloed models
- Require task-specific training
- Lots of human supervised training



Foundation models

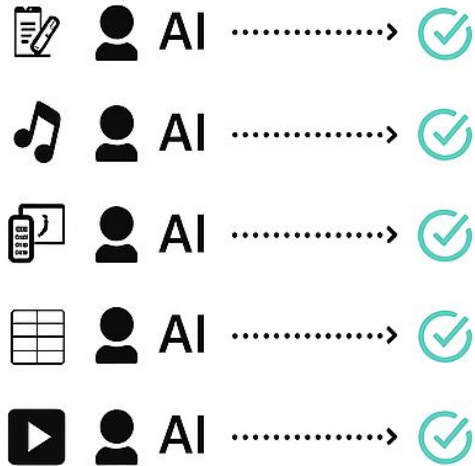
(E.g., Large Language Models: LLMs)



- Massive multi-modal model
- Adapted with minimal training
- Pre-trained unsupervised learning



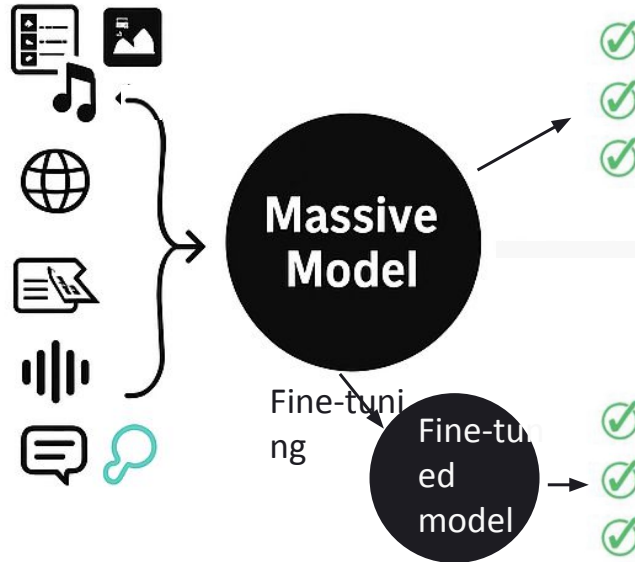
Traditional ML



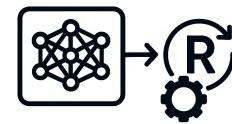
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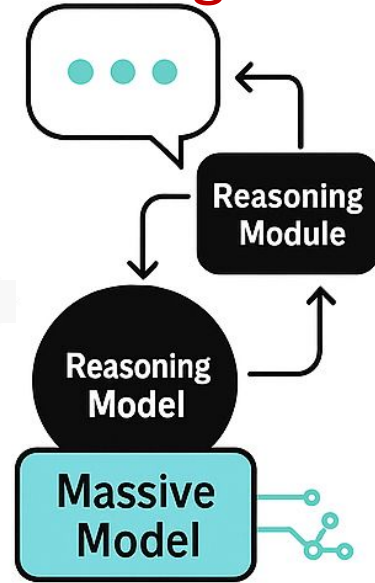
Foundation models (E.g., Large Language Models: LLMs)



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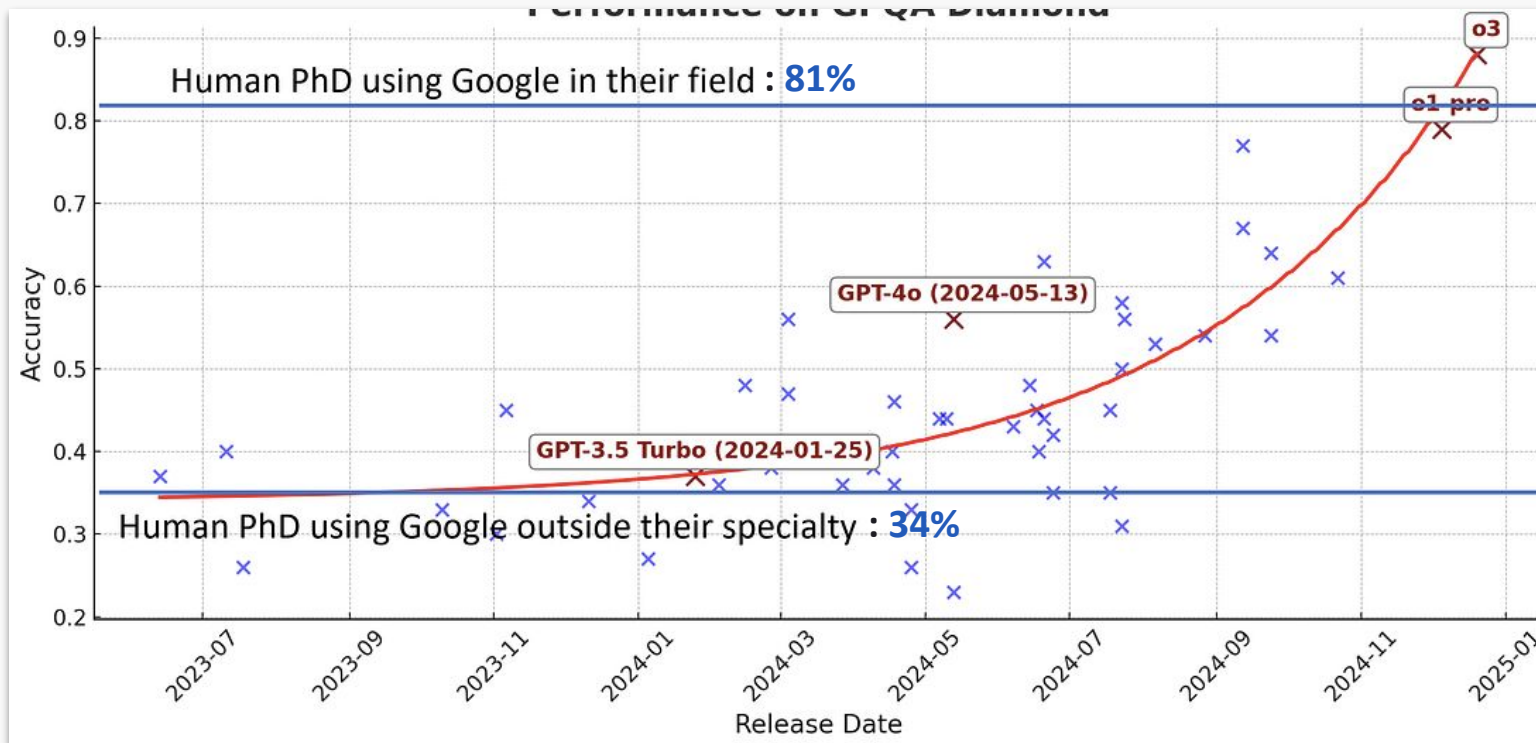


Reasoning models



- Deliberative multi-step logic
- Self-consistency checks
- Slower but more accurate inference

Graduate-Level Google-Proof Q&A test (GPQA), Diamond problems



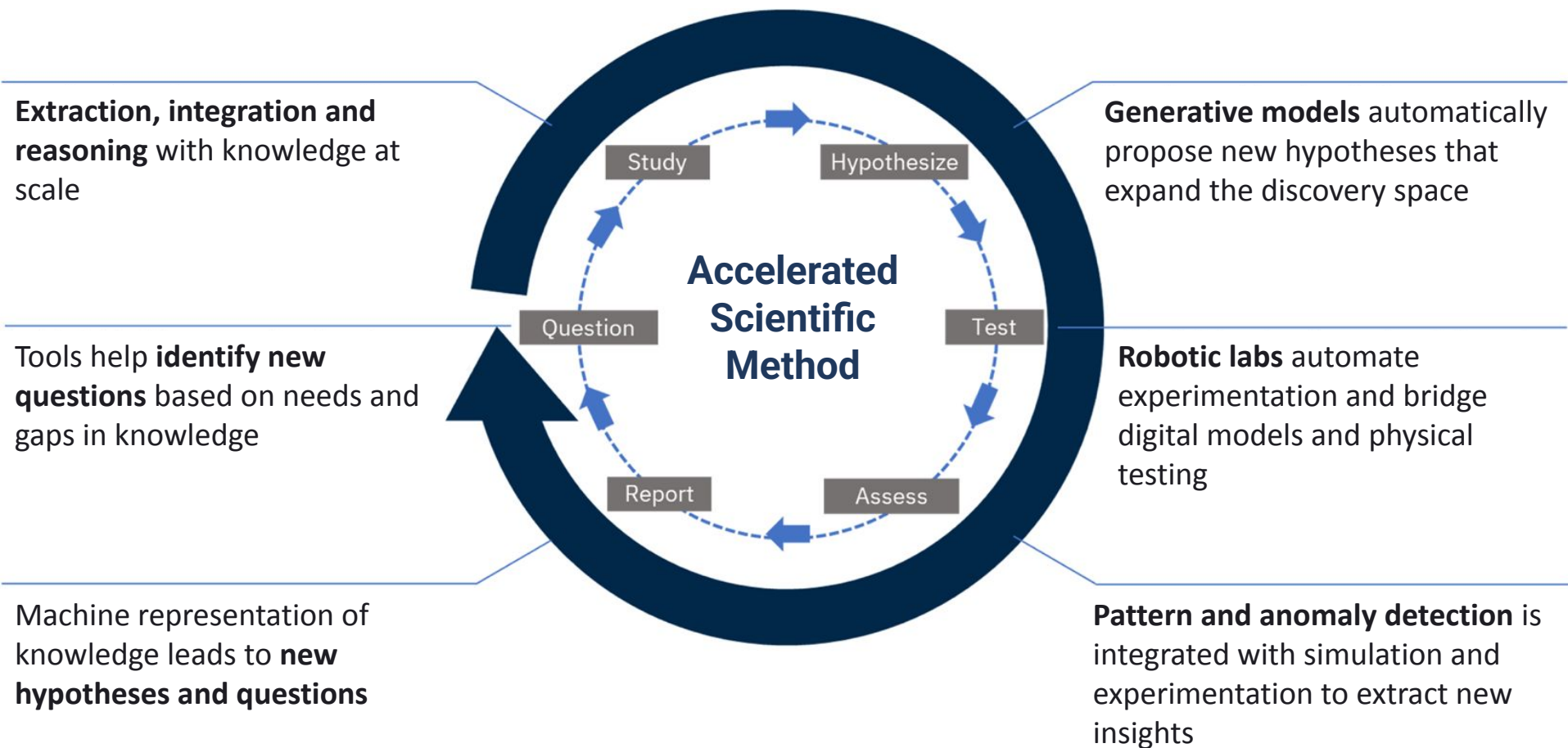
<https://arxiv.org/pdf/2311.12022>

<https://epoch.ai/data/ai-benchmarking-dashboard>

Overview

- What is an “agent”?
- LLMs, foundation models, reasoning models
- **Agents and scientific discovery**

Accelerating discovery in science



The emergence of LLM-based agents for science

“AI agents are autonomous systems that can **reason about tasks** and act to achieve goals by **leveraging external tools and resources**.

Modern AI agents are typically powered by large language models (LLMs) connected to external tools or APIs.

They can perform reasoning, invoke specialized models, and adapt based on feedback.

Agents differ from conventional “models” in important regards:

- They are interactive and adaptive
- Rather than returning fixed outputs, they can take multi-step actions, integrate context, and support iterative human–AI collaboration.
- Users can interact with them through human language, substantially reducing usage barriers for scientists.”

One agent or many?

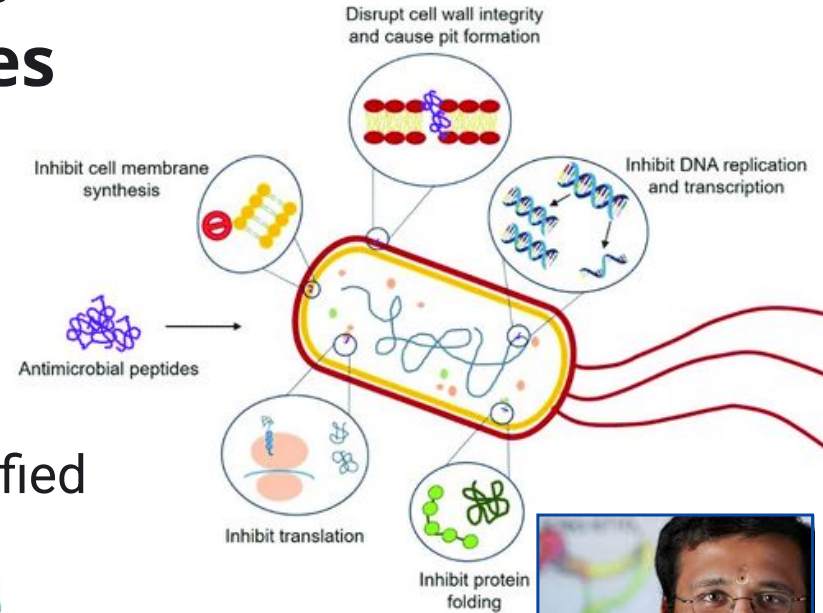
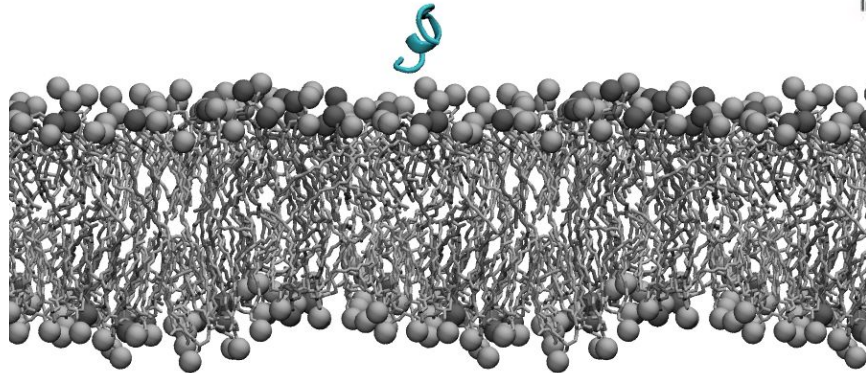
- In **principle**, a single reasoning model (like a single human) can apply a variety of different reasoning strategies, have specialized knowledge on different topics, improve expertise over time, etc.
- In **practice**, it is common to create multiple agents (like a team of people), e.g., for:
 - Modularity (specialization, reuse, maintainability)
 - Different roles (e.g., idea generator, idea critic, program generator, ...)
 - Parallelism (run multiple copies of an agent to explore different ideas)
 - Expanded capacity (e.g., larger LLM context)

An agentic architecture for the design of antimicrobial peptides

An antimicrobial peptide (AMP) is a short (typically 12 to 50 amino acid) molecule that can target and kill viruses, bacteria, fungi, and other pathogens

Challenge: Design an AMP that can kill specified bacterial strains without harming host cells

With 20 possible amino acids, there are $20^{20} = 10^{26}$ AMPs of length 20



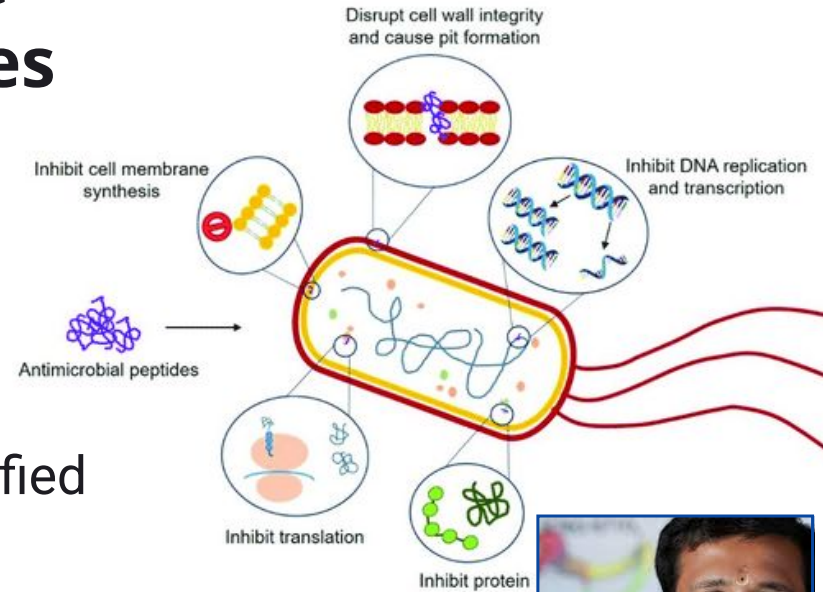
**Arvind
Ramanathan**

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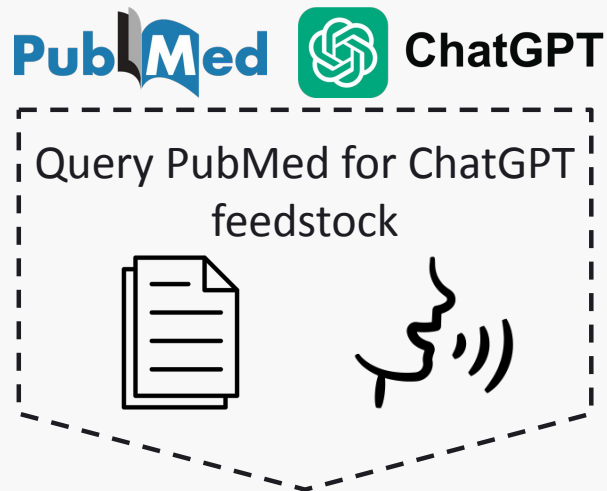
A rational design approach might combine knowledge of bacterial cell membrane composition and structure, AMP molecular and structural properties, host cell membrane characteristics and intracellular pathways—knowledge that may be gained by **database/literature search, simulation, experiment**



**Arvind
Ramanathan**

Example: A peptide expert

(Prototyped with PubMed and ChatGPT)



Retrieve abstract **A** from PubMed that reference specified **peptide**

Use ChatGPT to build hypotheses by using retrieval-augmented generation: e.g.:

“Given **A**, on which organism is {**peptide**} acting?”

We want a model with deep expertise regarding peptides and related topics

We want to be able to make millions of such requests

Arvind Ramanathan, Priyanka Setty, et al.

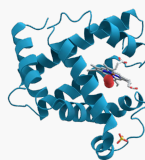
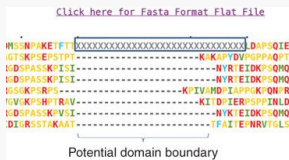
Define other agents, also foundation model-powered



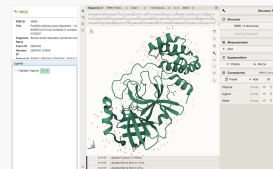
Query PubMed for ChatGPT feedstock



Align proteins, predict structure, rank results



Evaluate structures and filter results



Arvind Ramanathan, Priyanka Setty, et al.

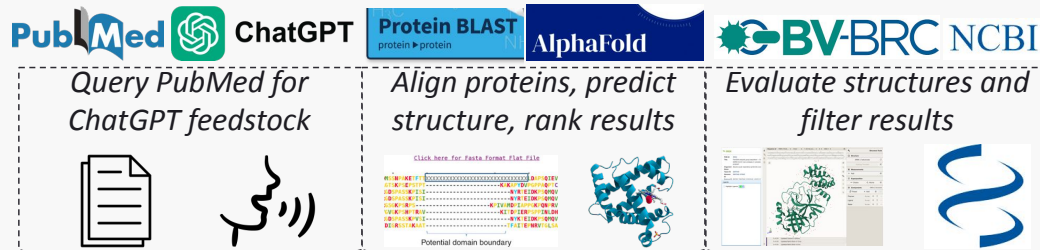


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Link agents into a flow

Input peptides



**Knowledge
agent**

**Structure
agent**

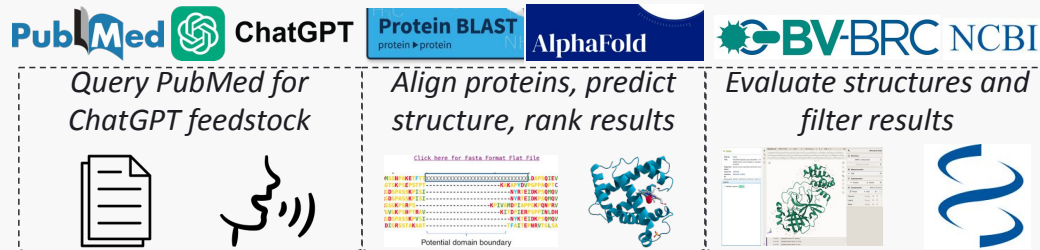
**Evaluation
agent**



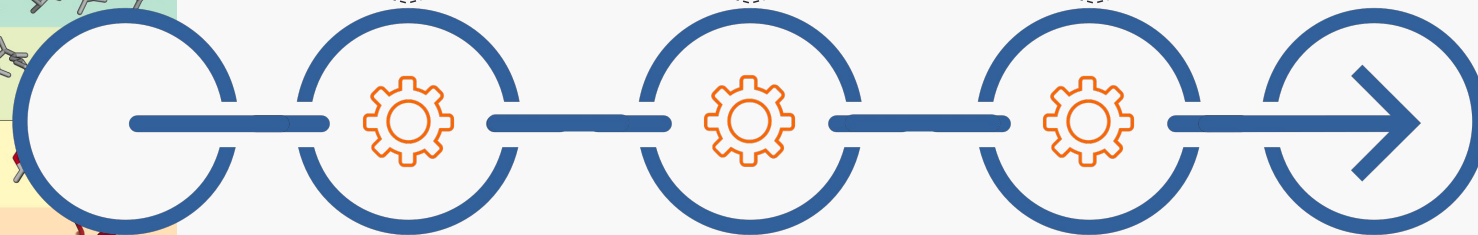
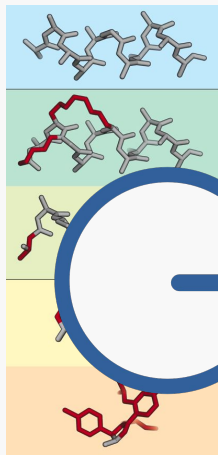
<https://globus.org>

Link with HPC for computational evaluation

Input peptides



**HPC
agents**



**Knowledge
agent**

**Structure
agent**

**Evaluation
agent**

*Computational
evaluation*

Arvind Ramanathan, Priyanka Setty, et al.



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Link with self-driving labs for experimental evaluation

Input peptides

PubMed ChatGPT

Query PubMed for
ChatGPT feedstock



Protein BLAST

AlphaFold

Align proteins, predict
structure, rank results

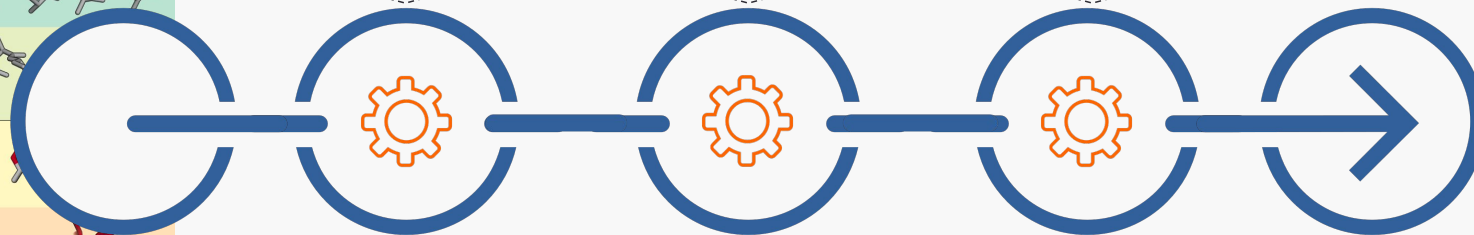
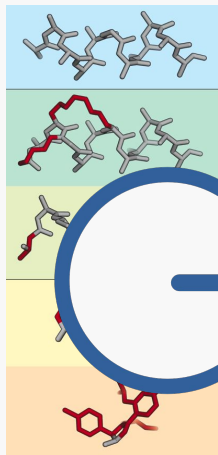


BV-BRC NCBI

Evaluate structures and
filter results



HPC
agents



Knowledge
agent

Structure
agent

Evaluation
agent

Experiment agents



Computational
& experimental
evaluation

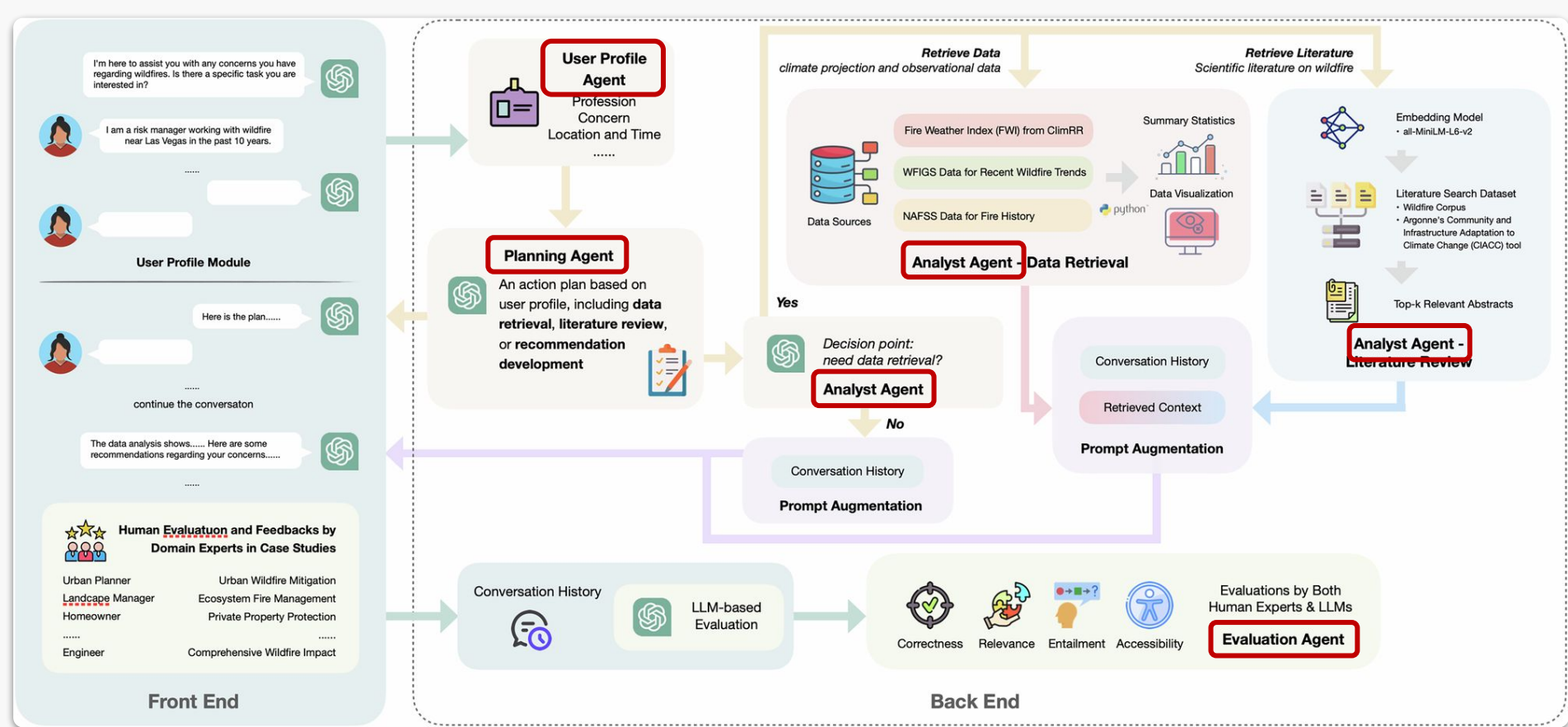


Arvind Ramanathan, Priyanka Setty, et al.



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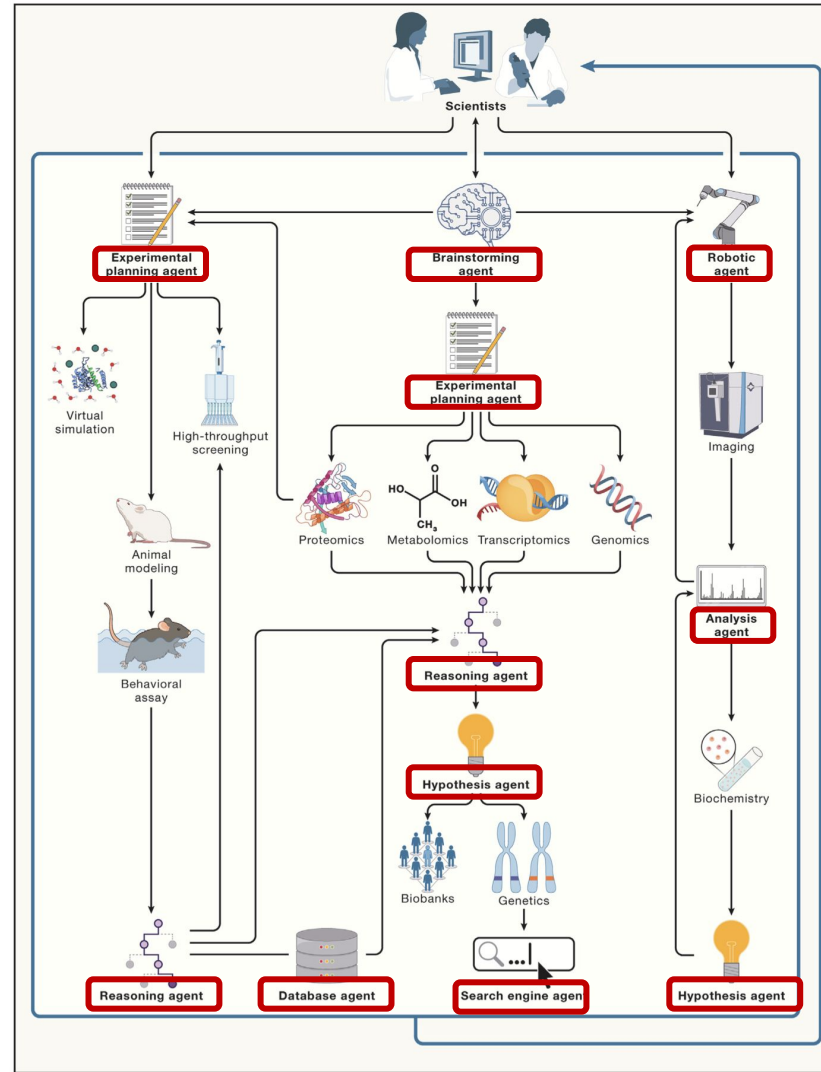
“MARSHA: multi-agent RAG system for hazard adaptation”

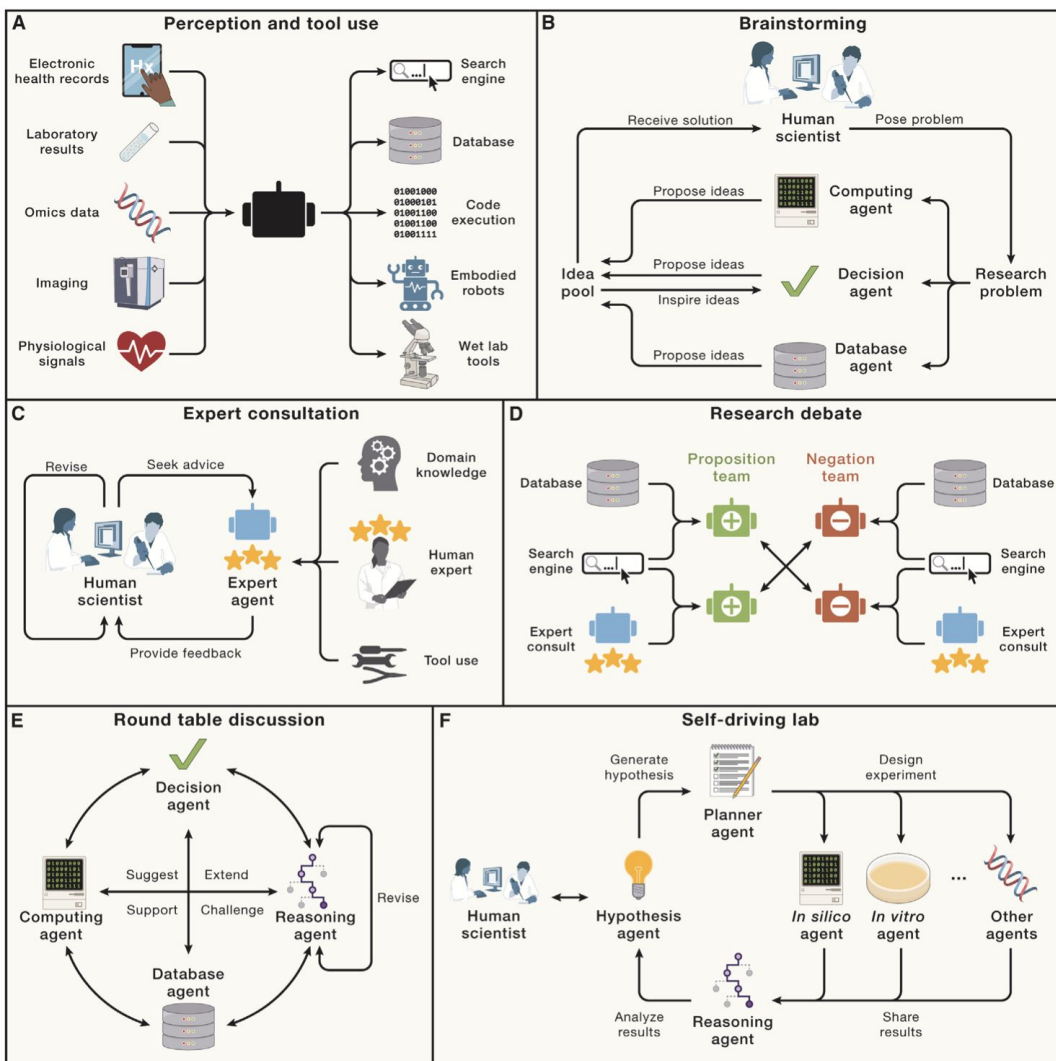
<https://www.nature.com/articles/s44168-025-00254-1>

Table 2: User profile variations and literature search queries in Phase 2 of the WildfireGPT personalization ablation study

Profession	Primary Concern	Scope	Search Query
Homeowner	Maximizing marketable species	Health and marketable species	“Strategies for managing forests to maintain health, maximize marketable species, and minimize wildfire risks in Virginia”
Civil Engineer	Ensuring structural and infrastructural resilience	Drainage efficiency and slope stability	“Wildfire risks and climate change impacts on forest management near Covington, VA; Strategies for enhancing drainage efficiency and slope stability; Structural resilience against wildfires in forested areas”
Ecologist	Maintaining biodiversity and ecosystem services	Ecological resilience and habitat connectivity	“Wildfire management and ecological resilience in forest ecosystems near Covington, VA”
Emergency Manager	Establishing defensible space and evacuation corridors	Emergency access and response capabilities	“Effective forest management practices, defensible space creation, evacuation protocols, and property protection measures against wildfires near Covington, VA”
Power Grid Manager	Maintaining transmission line clearance and grid resilience	Power distribution reliability and access	“Effective strategies for vegetation management, forest health maintenance, and wildfire risk mitigation around power grids near Covington, VA”

“Empowering biomedical discovery with AI agents”

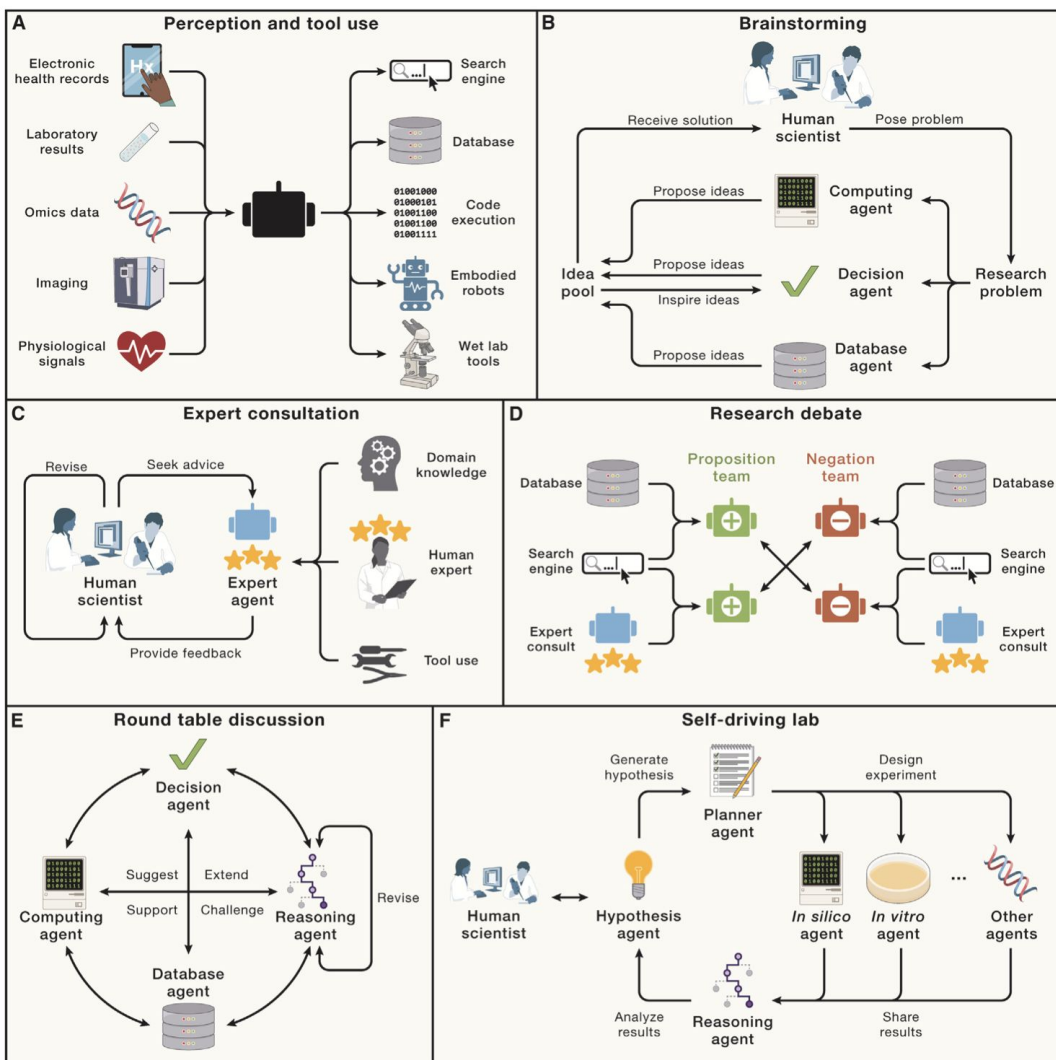




(A) By programming an LLM with the role, **one LLM-based agent**, equipped with memory and reasoning abilities, performs multimodal perception and utilizes a range of tools, e.g., web lab tools, to accomplish specified tasks.

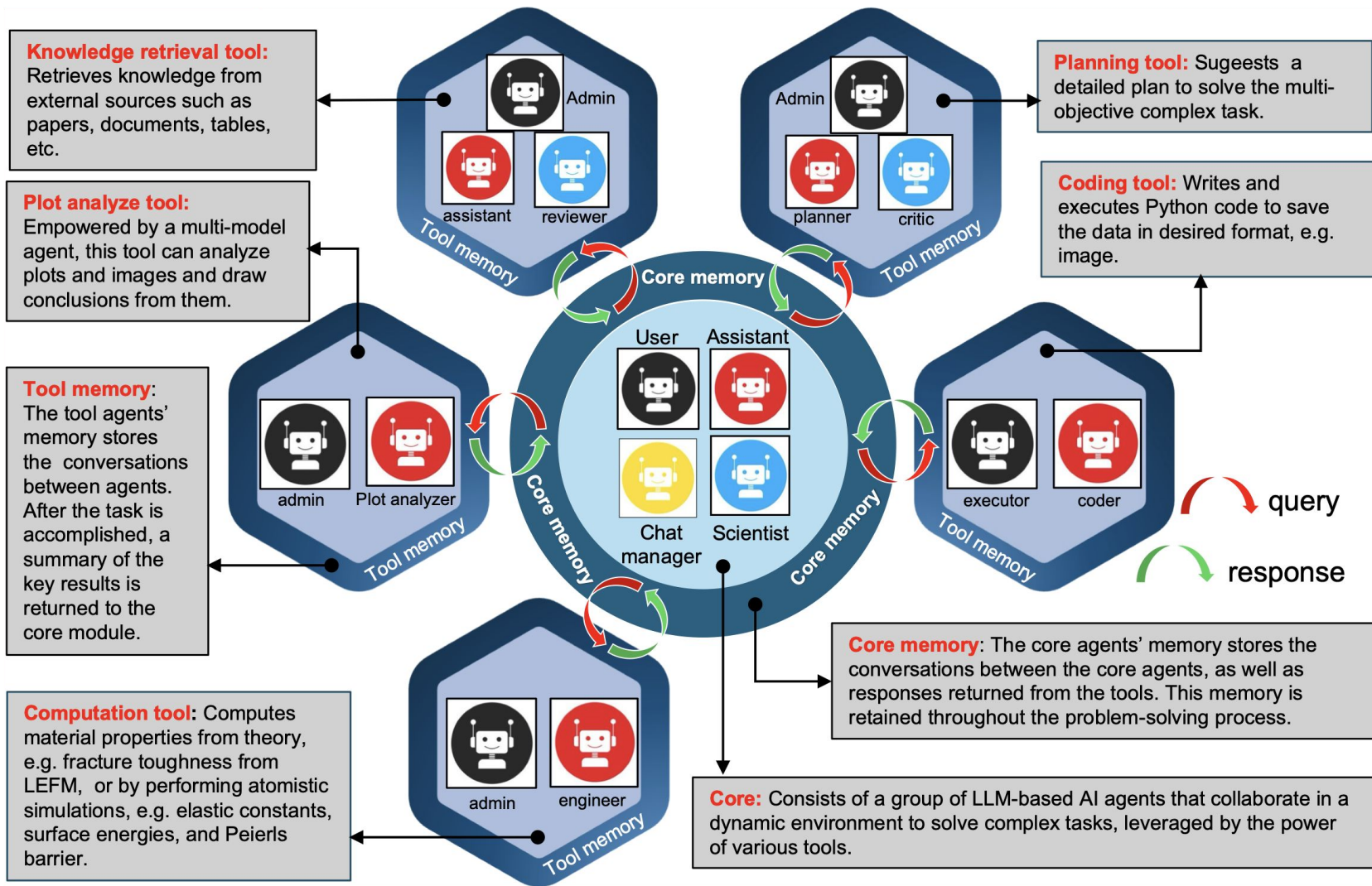
(B–E) Leveraging **AI agents equipped with diverse roles**, perception modules, tools, and domain knowledge enables collaboration between agents and scientists. This collaboration can adopt various configurations, such as expert consultation, debate, brainstorming, and roundtable discussions.

(F) **Multi-agent systems** can establish a self-driving laboratory wherein numerous agents collaborate on multiple iterations of biological research assisted by humans. Each cycle of research encompasses the generation of hypotheses, the design of experiments, the execution of experiments both in silico and in vitro, and the analysis of results.



- **Computing agent** utilizes computational models as tools
- **Decision agent** makes decisions in response to given conditions
- **Database agent** retrieves relevant information from databases
- **Reasoning agent** capable of direct reasoning and reasoning with feedback
- **Expert agent** provides professional consultation based on reliable sources, such as domain expertise, feedback from human experts, and results of specific tools
- **Hypothesis agent** capable of reflective learning and reasoning to generate hypotheses
- **Planner agent** devises plans for future actions
- **In silico/vitro agent** uses tools in silico or in vitro environment.

AtomAgents: Alloy design and discovery through physics-aware multi-modal multi-agent artificial intelligence

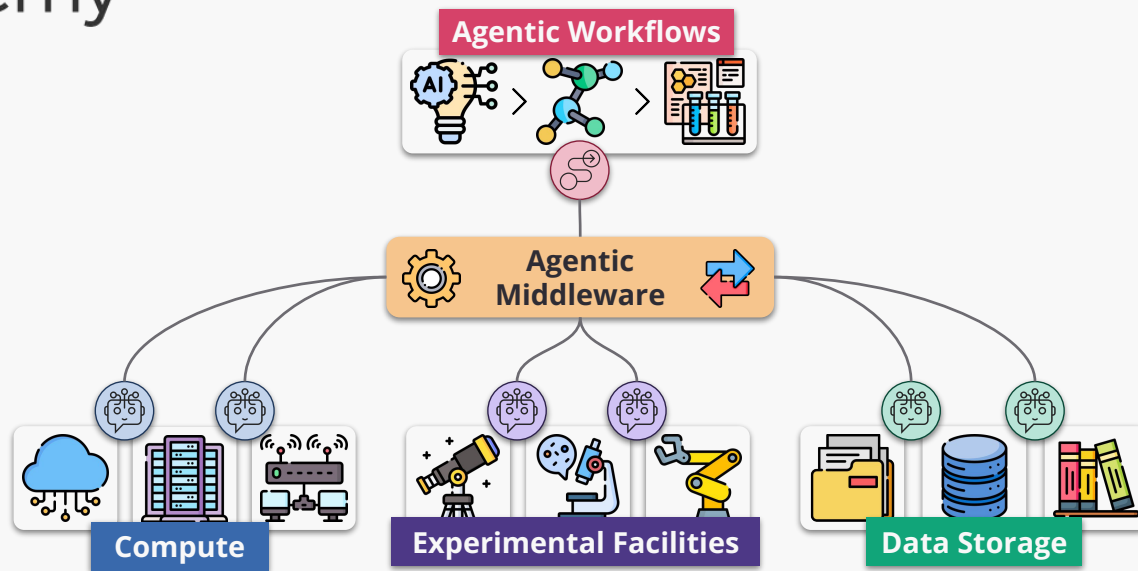


Questions?

Up next → Academy Overview

Academy Overview

9:00 – 9:30 am

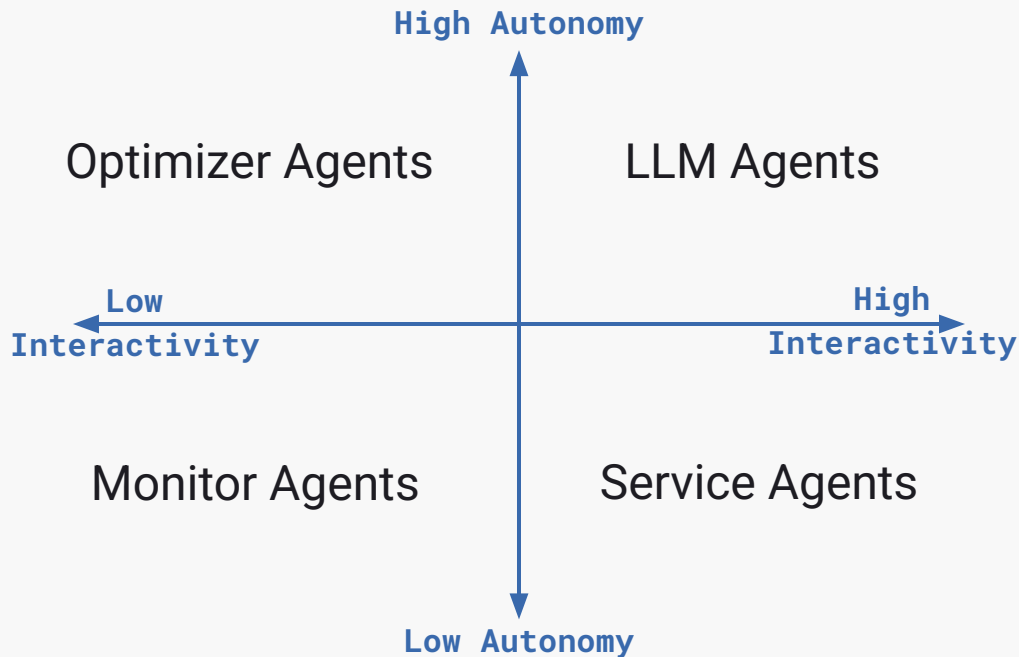


A middleware for building and deploying stateful actors and autonomous agents across distributed research infrastructure

Agentic Middleware

Software layer that transparently manages the lifecycle, communication, and coordination of autonomous agents across distributed computing environments.

Agentic Middleware: Agent Behaviors



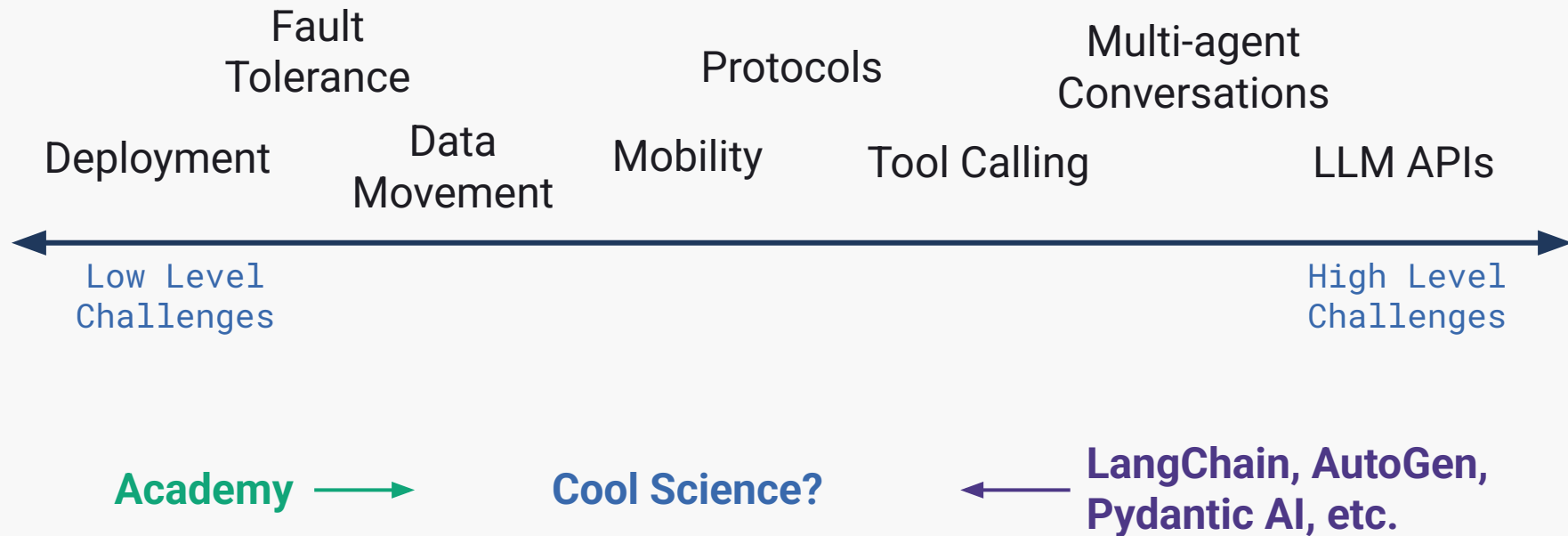
Other defining aspects:

- Persistent vs ephemeral
- General vs narrow purpose
- Embodiment

Long-running agentic science apps will incorporate many kinds of agent behaviors.

Academy primitives support the creation diverse agent types.

Agentic Middleware: Scope & Challenges



Agentic Middleware: Scope & Challenges

- Access & privileges
- Agent discovery
- Asynchronous communication
- Fault tolerance
- Interfaces ← *Initial focus areas*
- Mobility
- Persistent stateful execution
- Provenance
- Many more...

Agentic Discovery: Closing the Loop with Cooperative Agents

J. Gregory Pauloski, University of Chicago, Chicago, IL, 60637, USA

Kyle Chard, University of Chicago, Chicago, IL, 60637, USA

Ian Foster, Argonne National Laboratory, Lemont, IL, 60439, USA

Abstract—As data-driven methods, artificial intelligence (AI), and automated workflows accelerate scientific tasks, we see the rate of discovery increasingly limited by human decision-making tasks such as setting objectives, generating hypotheses, needed to a
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and machine learn



FIGURE 2. The scientific method is an iterative process (stages depicted in the central loop). Specialized agents (depicted as boxes with corresponding stages indicated by color) can carry out the stages autonomously. Agents can also transcend stages to enable long-term planning, exploration, and safety.

Published in IEEE Computer Oct 2025

<https://arxiv.org/abs/2510.13081>

Agentic Middleware: Using Research Infrastructure

Centralized

- Agents co-located (workstation, cloud)
 - Research infrastructure available via APIs (REST, SDKs, MCP Servers, ...)
 - Use infrastructure via tool calling
- ++ Rapidly growing library ecosystem
- Limited APIs for infrastructure

**LangChain, AutoGen,
Pydantic AI, etc.**

Decentralized

- Agents distributed across infrastructure
 - Agents interact asynchronously
 - Use infrastructure directly (actuate a robot, submit job, ...)
- ++ Data locality, perf., loose coupling
- Deployment complexity

Academy

How does **Academy** support the expression of **diverse agent behaviors** and deployment across **distributed/federated resources**?

Requirements

- Federated orchestration
- Configurable data plane
- Temporally decoupled messaging
- Agent authentication and permissions
- Resilient state management

Inspiration

Workflows

Dask, Parsl, Pegasus

- ++ Task automation
- ++ Distributed task execution

Actor Systems

Akka, Dask, Ray

- ++ Stateful computation
- ++ Actor-to-actor interaction

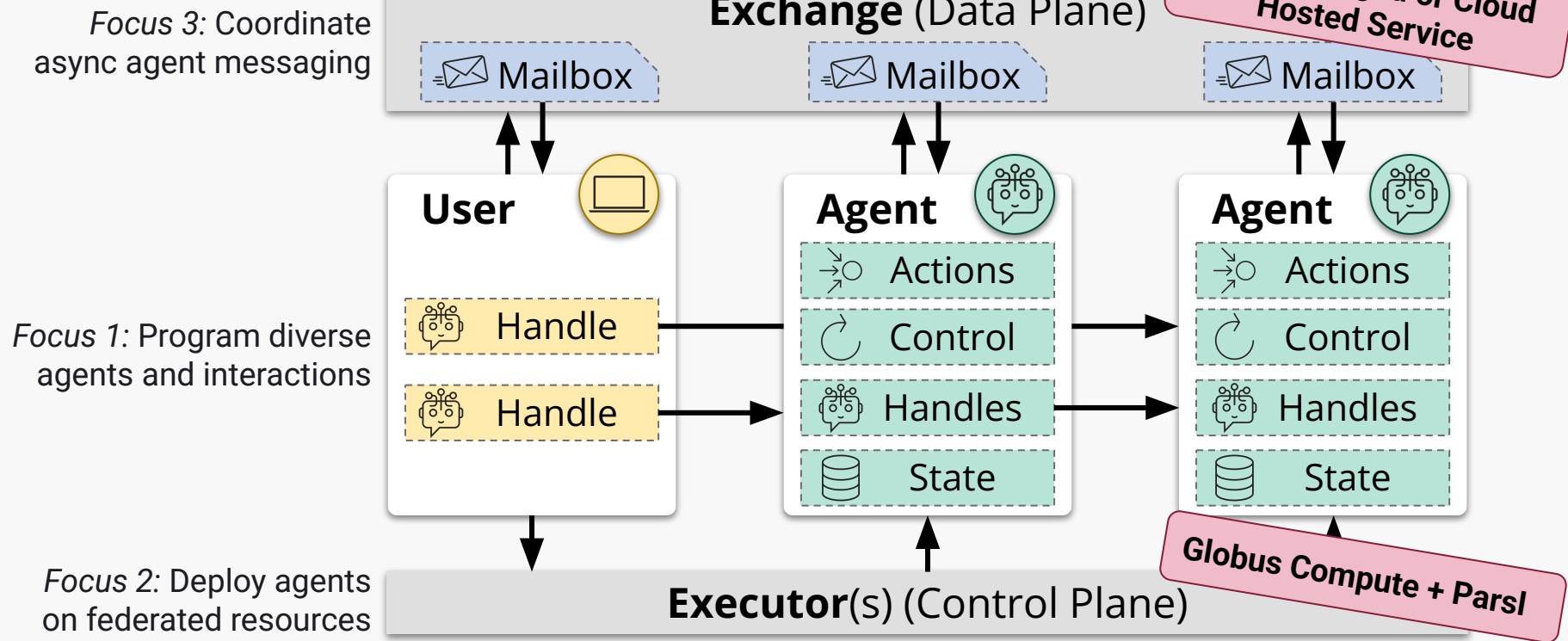
Function-as-a-Service

Globus Compute, Lambda

- ++ Remote execution
- ++ Fire-and-forget model

Academy

- *Fire-and-forget*: Agents spawned across remote/federated resources
- *Autonomy*: Agents have agency over their actions and local state/resources
- *Cooperative*: Agents interact to execute tasks & workflows



<https://docs.academy-agents.org/latest/concepts/>

Diverse Communication Options

Local Exchange

- In-memory, no setup, for local applications or fast debugging

Hybrid Exchange

- Direct communication first, with mediated fallback for resilience
- Leverage high-speed interconnects within clusters/sites

Cloud Exchange + Proxystore

- Http service authenticated with Globus
- Secure multi-site applications

* Proxystore: Pass-by-reference semantics for transferring large objects

Accelerating Communications in Federated Applications with Transparent Object Proxies

J. Gregory Pauloski
University of Chicago

Valerie Hayot-Sasson
University of Chicago

Logan Ward
Argonne National Laboratory

Nathaniel Hudson
University of Chicago

Charlie Sabino
University of Chicago

Matt Baughman
University of Chicago

Kyle Chard
Argonne National Laboratory

Ian Foster
University of Chicago

Argonne National Laboratory

ABSTRACT
Advances in networks, accelerators, and cloud services encourage programmers to reconsider where to compute—such as when fast networks make it cost-effective to compute on remote accelerators despite added latency. Workflow and cloud-hosted serverless computing frameworks can manage multi-step computations spanning federated collections of cloud, high performance computing (HPC), and edge systems, but passing data among computational steps via cloud storage can incur high costs. Here, we overcome this obstacle with a new programming paradigm that decouples control flow from data flow by extending the pass-by-reference model to distributed applications. We describe Proxystore, a system that implements this paradigm by providing object proxies that act as wide-area object references with just-in-time resolution. This proxy



Fig. 1. Proxystore architecture. The diagram shows a Producer (green box) sending data to a Proxy (blue box), which then sends it to a Proxystore (purple box). The Proxystore then sends data to a Consumer (green box). The Proxy and Proxystore are connected by a bidirectional arrow. The Proxystore is also connected to a cloud storage icon (blue cloud) and a server icon (blue server). The Proxy is connected to a server icon (blue server). The Producer and Consumer are connected to a server icon (blue server).

SC23
Denver, CO | i am hpc.

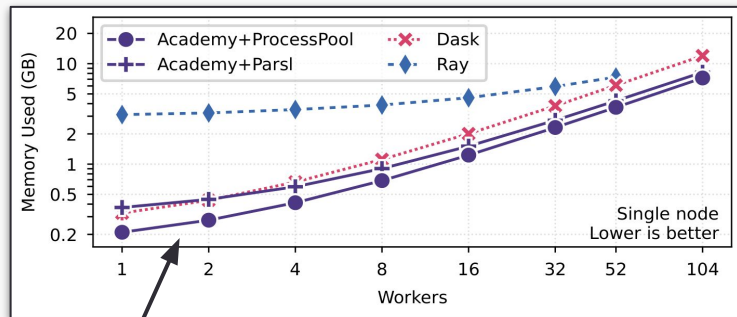


Features (rapid fire)

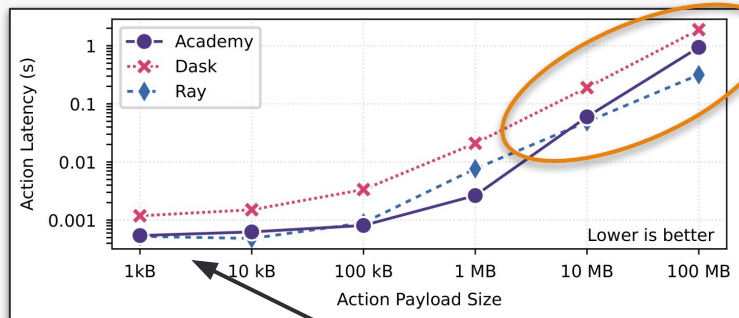
- Any number of actions & control loops
- Special purpose control loop decorators
- Async/non-blocking action execution
- Startup and shutdown callbacks
- State persistence plugins
- Re-execution on failure
- Agents can launch other agents
- Discovery/lookup based on behavior

Comparisons to Actor Systems

Why we need ProxyStore!

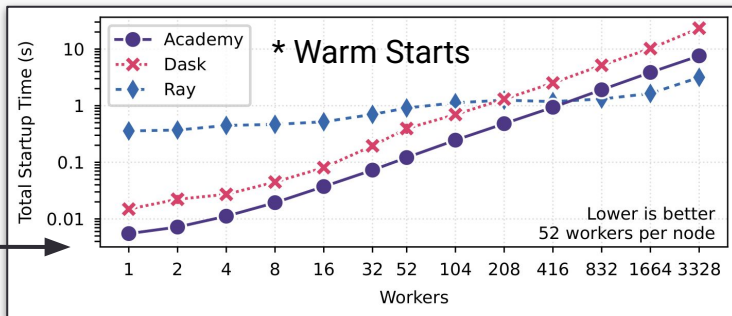


Low-memory overhead



Low-latency messaging

Fast start-up



Experiments performed on Aurora @ ALCF

Writing Apps in Academy

Agents defined
by a class

Clients & other
agents can
request actions

```
import asyncio
from academy.agent import Agent, action, loop

class Example(Agent):
    def __init__(self) -> None:
        self.count = 0 # State stored as attributes

    @action
    async def square(self, value: float) -> float:
        return value**2

    @loop
    async def count(self, shutdown: asyncio.Event):
        while not shutdown.is_set():
            self.count += 1
            asyncio.sleep(1)
```

Instance of a
agent is state

Control loops for
autonomous
behavior

<https://docs.academy-agents.org/stable/get-started/>

Single interface
for managing
your agents

Launch agent
and get handle

Interact with
agents via
handles

```
from academy.exchange import HybridExchangeFactory
...
from academy.manager import Manager
```

```
gce = GlobusComputeExecutor('<UUID>')
```

```
async with await Manager.from_exchange_factory(
    factory=HybridExchangeFactory(),
    executors=gce,
) as manager:
```

```
    behavior = Example() # From the prior slide
    handle = await manager.launch(behavior)
```

```
    result = await handle.square(2)
    assert result == 4
```

```
    await handle.shutdown()
```

Launch agents via
Globus Compute

<https://docs.academy-agents.org/stable/get-started/>

Call sync
libraries from
async actions

```
from academy.agent import Agent, action
from academy.handle import Handle

class Coordinator(Agent):
    def __init__(self, simulator: Handle[Simulator]) -> None:
        self.simulator = self.simulator

    def process(self, result: Result) -> Result: ...

    @action
    async def compute_property(self, smiles: str) -> float:
        result = await self.simulator.simulate(smiles)
        # Run sync code in thread
        processed = await self.agent_run_sync(self.process, result)
        return processed
```

Pass handles to
other agents or
between
processes

Integrating Academy and LLMs

```
from academy.handle import Handle
from langchain_core.tools import tool

def make_sim_tool(handle: Handle[MySimAgent]):
    @tool
    async def compute_property(smiles: str) -> float:
        """Compute molecule property."""
        return await handle.compute_property(smiles)
    return compute_property

tool = make_sim_tool(agent_handle)
print(tool.args_schema.model_json_schema())
```

Turn agent handles into LLM
framework “tools”

Comparison to Alternatives

Tool Servers (MCP)

Academy-MCP Plugin

Rely on externally reachable endpoints
that are blocked by facility policies.
Requires user to manage services,
infrastructure, and VPNs

Func-as-a-Service (Globus Compute)

Easier remote execution (no VPN,
infrastructure management) but tools
must be stateless, short-running tasks

Recap

Build

- Unified framework for creating diverse, stateful, and autonomous agents

Deploy

- Run and coordinate agents seamlessly across federated HPC resources

Integrate

- Connect agents with LLMs, MCP servers, instruments, robots, and more

Evolve

- Design agentic workflows that are composable, resilient, and self-managing

Next we'll build some some simple agents

Questions?

Up next → Hands-on: Getting Started

Hands-on: Getting Started

9:30 – 10:00 am

Setup

Checkout the tutorial repo

```
$ git clone https://github.com/academy-agents/academy-tutorial  
$ cd academy-tutorial
```



Install dependencies in a virtual environment



Native

```
$ python -m venv venv  
$ source venv/bin/activate  
$ pip install -e .
```



Conda

```
$ conda create -n academy python=3.12  
$ conda activate academy  
$ pip install -e .
```



UV

```
$ uv venv --python 3.12  
$ source .venv/bin/activate  
$ uv pip install -e .
```

Your First Academy Application

Goal: Write an Counter Agent

- **State:** Count
- **Actions:** Increment, Get_Count
- **Tips:**
 - Use `LocalExchangeFactory` for communication
 - Use `ThreadPoolExecutor` for launching

Define an agent class with state

```
import asyncio
from academy.agent import Agent, action, loop

class Example(Agent):
    count: int

    async def agent_on_startup(self) -> None:
        self.count = 0

    @action
    async def increment(self, value: int = 1) -> None:
        self.count += value

    @action
    async def get_count(self) -> int:
        return self.count
```

Actions define methods that can be invoked over the exchange

State can be initialized on `__init__` or with `on_startup` method

Manage the
launch and
communication
of agents

```
from academy.exchange.local import LocalExchangeFactory
from academy.manager import Manager

async with await Manager.from_exchange_factory(
    factory=LocalExchangeFactory(),
    executors=ThreadPoolExecutor(),
) as manager:
    handle = await manager.launch(Example)

    await handle.increment()
    result = await handle.get_count()
    assert result == 1
```

Launch agent
and get handle

Interact with
agents by
invoking actions

Adding a Control Loop

Goal: Add “autonomous” behavior to agents

Change increment to count every second

```
import asyncio
from academy.agent import Agent, action, loop

class Example(Agent):
    ...
    @loop
    async def increment(self, shutdown: asyncio.Event):
        while not shutdown.is_set():
            await asyncio.sleep(1)
            self.count += 1
```

Agent Cooperation

Goal: Call agent internally from another agent

- Create a Coordinator Agent
 - **Actions:** process: lowers and reverses a string
 - Use **Lowerer** and **Reverser** to accomplish task

Handles bind to
mailboxes
based on
context

```
import asyncio
from academy.agent import Agent, action

class Coordinator(Agent):
    def __init__(self, lowerer, reverser):
        self.lowerer = lowerer
        self.reverser = reverser

    @action
    async def process(self, text: str) -> None:
        reversed = await self.reverser(text)
        return await self.lowerer(reversed)
```

Pass Agent
handles

Agents can
communicate
via the
exchange too!

```
from academy.exchange.local import LocalExchangeFactory
from academy.manager import Manager

async with await Manager.from_exchange_factory(
    factory=LocalExchangeFactory(),
    executors=ThreadPoolExecutor(),
) as manager:
    ...
    coordinator = await manager.launch(
        Coordinator,
        args=(lowerer, reverser),
    )
    ...
    result = await coordinator.process(text)
    print(result)
```

Agent initialized
with handle



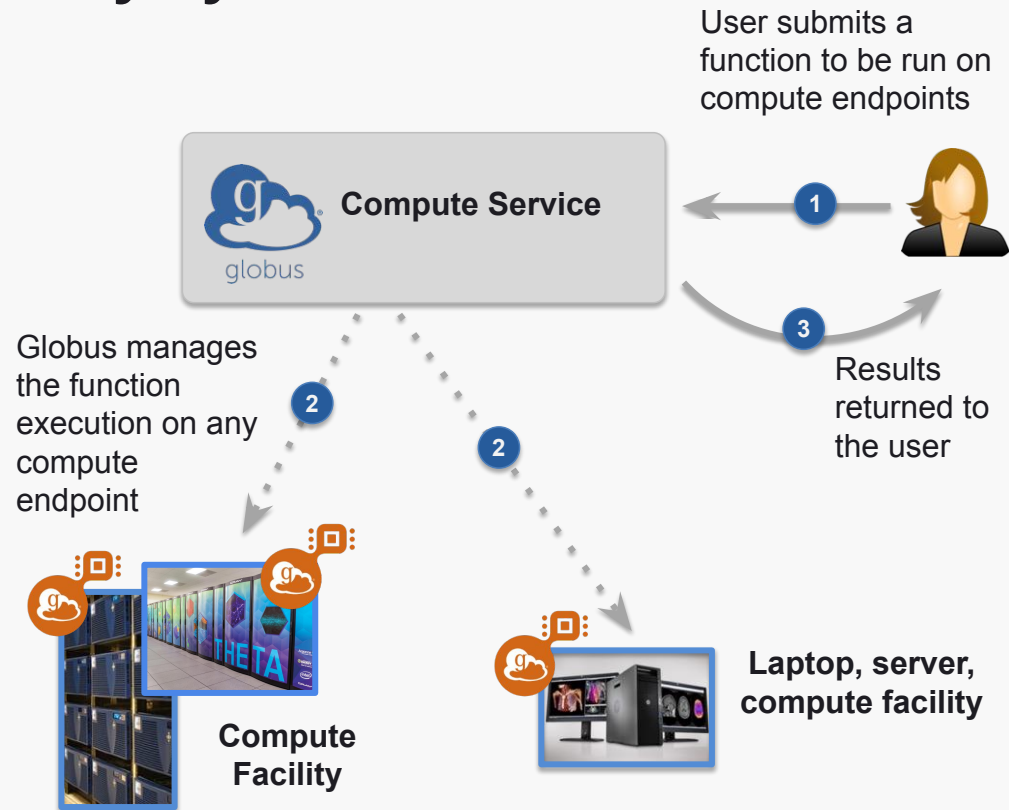
Launching agents

Goal: Launch agents on remote computers

- Academy supports various methods of deploying agents
 - Manual: `Runtime.run_until_complete()`
 - Thread/Processes: local deployment
 - Parsl: scalable deployment on HPC systems
 - Globus Compute: distributed and scalable deployment on arbitrary systems

Managed compute ...on any system

- Support use of Python for functions
- Fire and forget function execution
- Federated authentication, and local access control
- Uniform interface to various compute resources





Globus Compute

FaaS Service + “bring-your-own compute” model

1. Deploy “endpoint” on Cluster or Laptops
2. Define python function for remote execution
3. Submit function to cloud service

```
pip install globus-compute-endpoint==3.16.1
globus-compute-endpoint configure
globus-compute-endpoint start <ENDPOINT_NAME>
export ACADEMY_TUTORIAL_ENDPOINT=<ENDPOINT_ID>
```

Try it!

```
from globus_compute_sdk import Executor

def hello_world():
    return "Hello World!"

tutorial_endpoint_id = '707fe7ed-6f06-4ec3-877f-1c1f0e9aeb84'
with Executor(endpoint_id=tutorial_endpoint_id) as fxe:
    future = fxe.submit(hello_world)
    print(future.result())
```


Distributing Agents

Goal: Run and Communicate with Agents in the Cloud

- Use **HttpExchangeFactory** for communication

```
HttpExchangeFactory(  
    url='https://exchange.academy-agents.org',  
    auth_method='globus'  
)
```

- Use **GlobusComputeExecutor** for launching

```
GlobusComputeExecutor('<YOUR_ENDPOINT_ID>')
```

Break

10:00 – 10:30 am

Agentic Workflows for Science

10:30 – 10:45 am

Replacing the Human-in-the-Loop

Humans synthesize knowledge and propose hypotheses

Humans write, debug, and run programs

Humans interpret results to inform new hypotheses

Inefficient use of
research infrastructure

Agents can be the driving entities

→ Persistent, stateful, cooperative

→ Intermittent human oversight

We need to be here

Credit: Ian Foster, “**Empowering Science with Intelligent Middleware and Embodied Agents**”

Agentic Workflows for Science

- ✓ Automate closed-loop processes
- ✓ Natural expression of scientific resources (compute, instruments, repositories)
- ✓ Operate autonomously but still cooperatively
- ✓ Execute multi-stage computational science processes
- ✓ Reduce mundane tasks & responsibilities of scientists

The whole is greater than the sum of its parts.

- Aristotle

Agentic Patterns Beyond LLMs

Conversational Assistants

Human

Provide the SMILES string corresponding to this molecule: 1-(2-methylphenyl)-3-(3-methylpyridin-2-yl)urea

ChemGraph

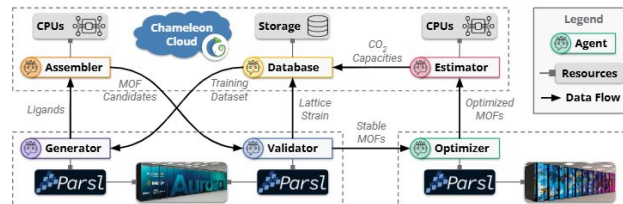
I'll help you find the SMILES string for the molecule 1-(2-methylphenyl)-3-(3-methylpyridin-2-yl)urea. To do this, I'll use the molecule_name_to_smiles function. However, in this case, the input is a systematic chemical name rather than a common molecule name, so the function might not work directly.

[...]

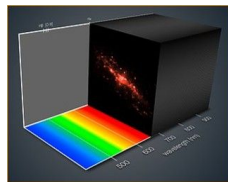
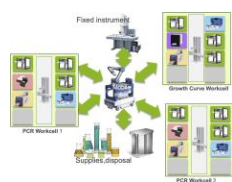
Would you like me to help you find alternative ways to represent this molecule?

Human

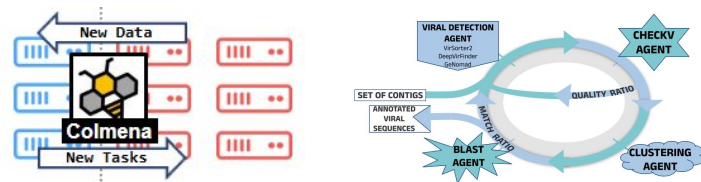
Multi-Site Applications



Integrating Instruments/Experiments



Steering Workflows

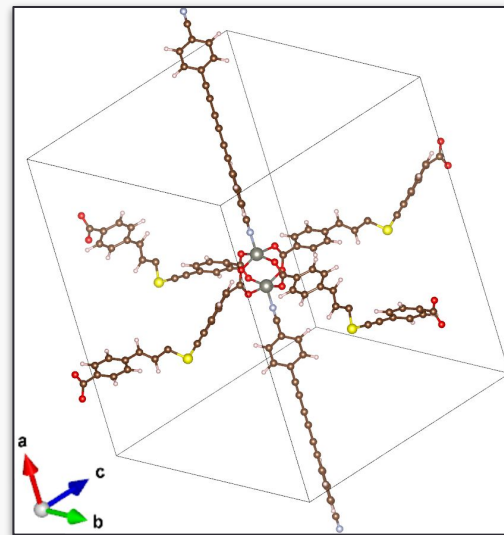


Use Case: MOF Discovery

Metal Organic Frameworks (MOF)

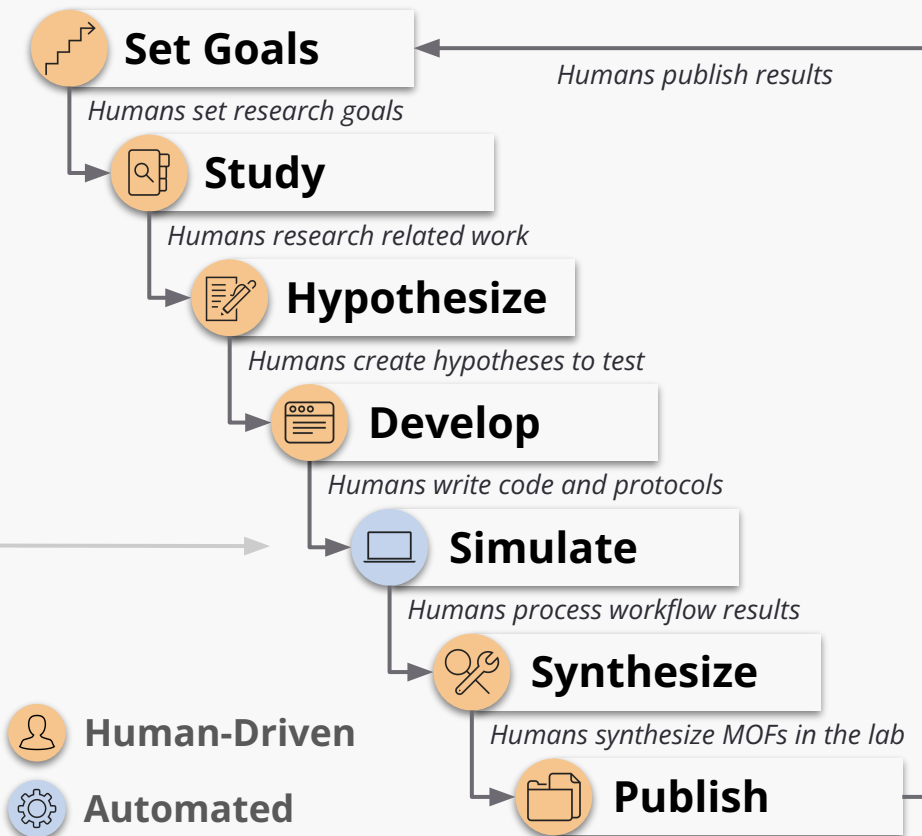
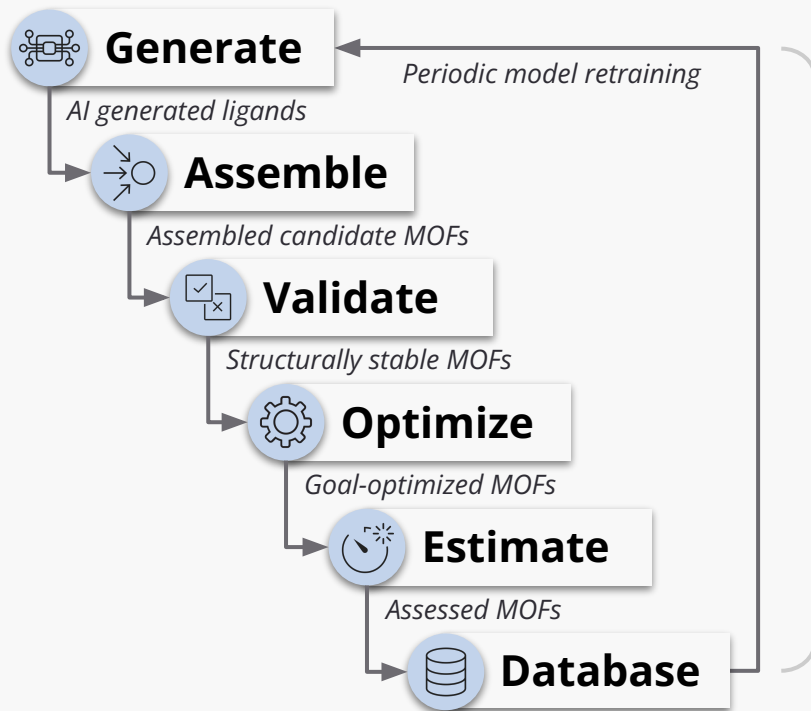
- Composed of organic molecules (ligands) and inorganic metals (nodes)
- The sponges of materials science!
- Porous structures that adsorb and store gases
- Topologies can be optimized for targeted gas storage → **Carbon Capture**

How to efficiently discover MOFs with desirable properties for target applications?

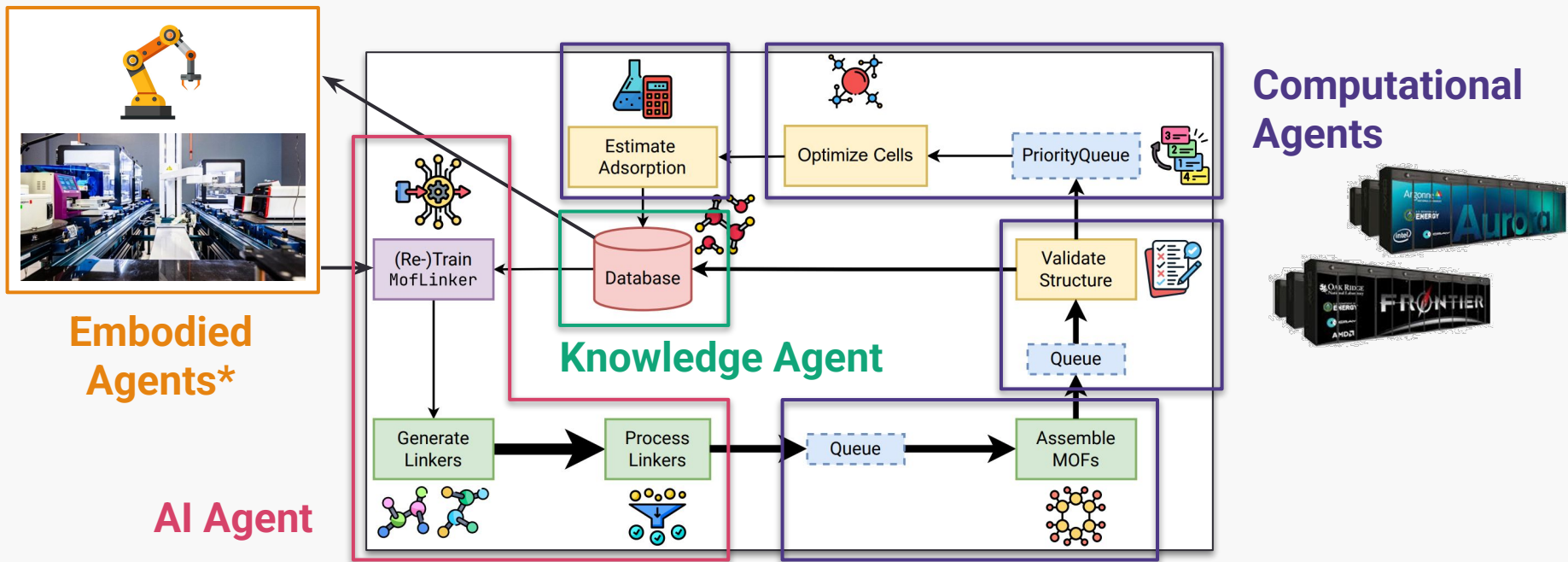


Intractable search space of ligand, node, & geometry combinations

Closed Loop Workflows

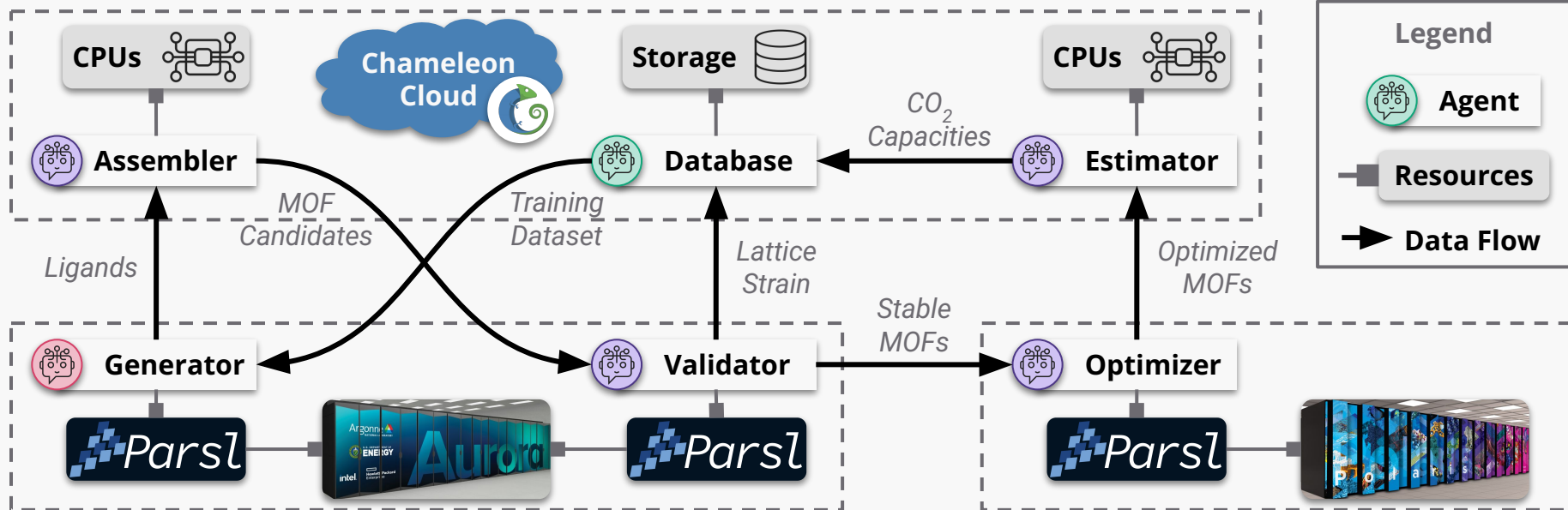


MOFA: Online learning + GenAI + Simulation

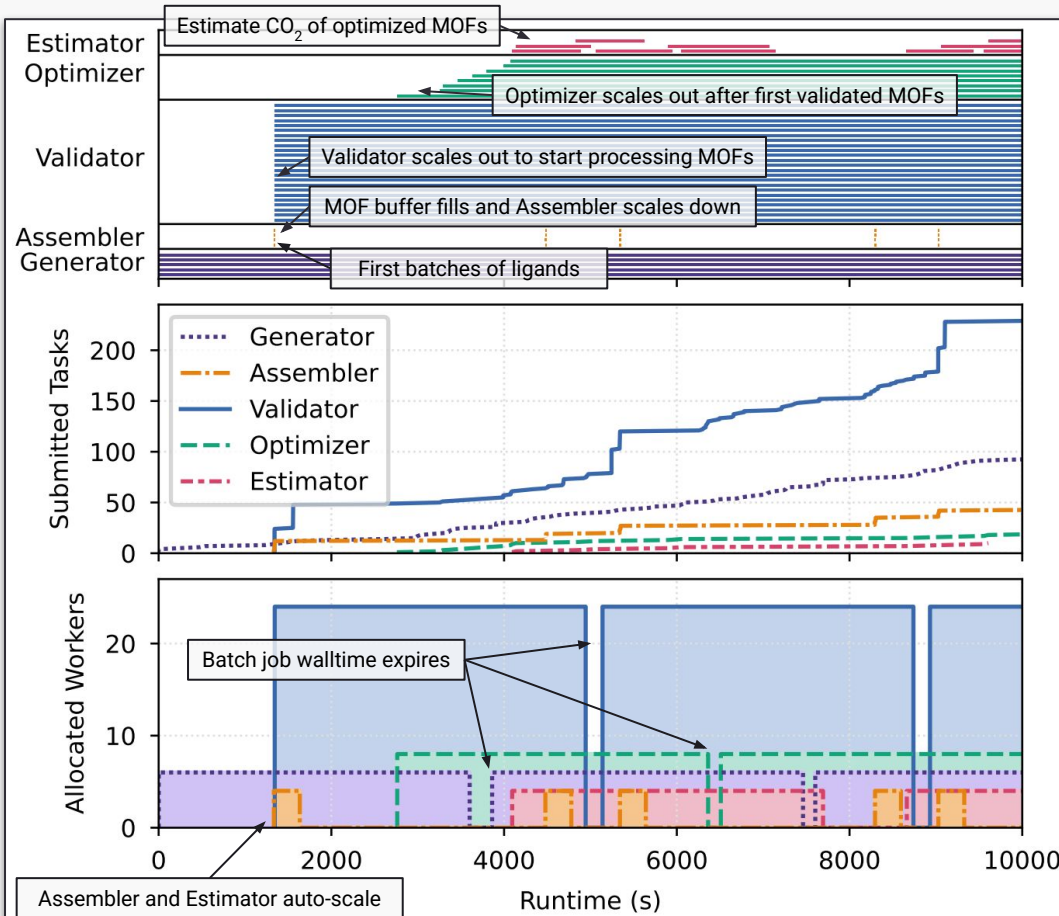


Yan et al., "MOFA: Discovering Materials for Carbon Capture with a GenAI- and Simulation-Based Workflow" (Under Review)

MOFA through Autonomous Agents



Agents executed remotely via Globus Compute



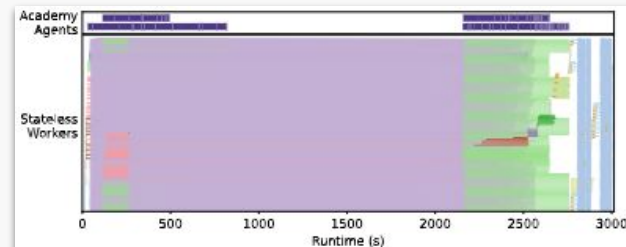
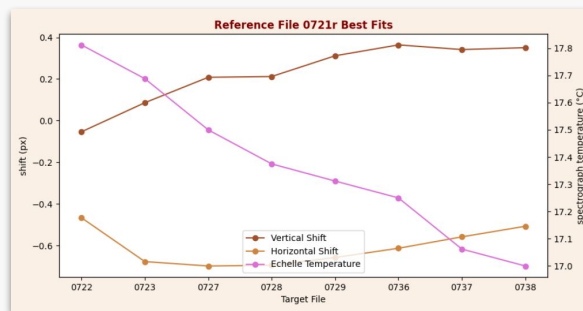
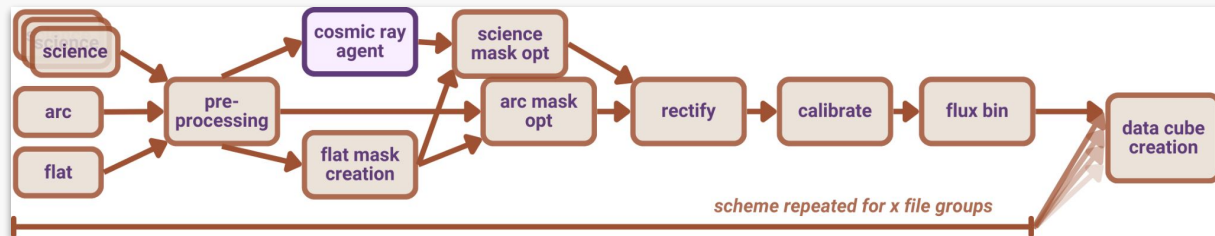
MOFA Agents Trace

Why is this agentic model better?

- **Placement:** Move agents to resources
- **Separation of concerns:** Resource acquisition and scaling based on local workload
- **Loose coupling:** Swap agents or integrate new agents (e.g., SDL)
- **Shared agents:** Multiple workflows can share agents (microservice-like)

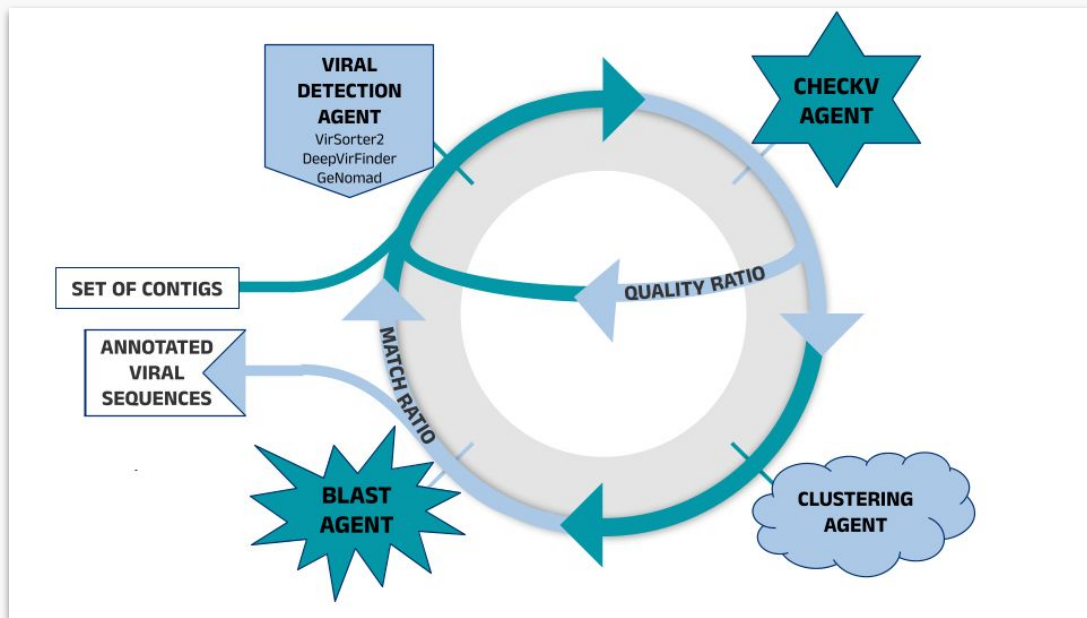
Use Case: Integral Field Unit Spectroscopy

- Highly-sensitive to instrument calibration
- Optical parameters are **continuous in time**
- Resolution and speed can be improved using **stateful processing**



Use Case: Viral Microgenomics

- Multiple tools exist to complete the same tasks (i.e. viral detection)
- Workflow construction is manual and heuristic
- Can we learn from downstream metrics to automate workflow design?



The Future? The Scientific Method through Agents



Questions?

Up next → Hands-on: Battleship

Hands-on: Battleship

10:45 – 11:30 am

Example: Battleship (30 Minutes)

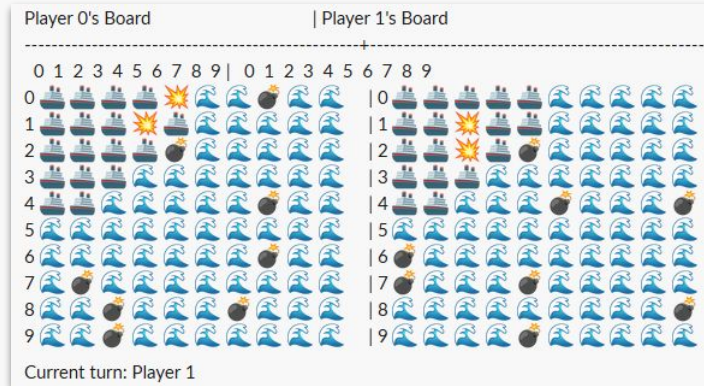
Battleship Rules:

- 10 x 10 grid of coordinates
- Each player has 5 “ships”
 - a. A ship is a continuous run of coordinates
- To start each game, a player places ships on grid
- On each turn:
 - a. Guess coordinate on opponents grid
 - b. Recieve if guess was a hit or miss



Example: Battleship (30 Minutes)

1. Open the starter code from the repo.
2. Battleship Data Structures
 - Board
 - Game
3. Understand the Coordinator class
 - game - Runs a single game between two Player agents
 - play_games - Repeatedly plays games between two Players
4. Implement BattleshipPlayer
 - get_move - Choose coordinates of next attack
 - new_game - Place ships on new board



Battleship Extensions

Strategy Ideas:

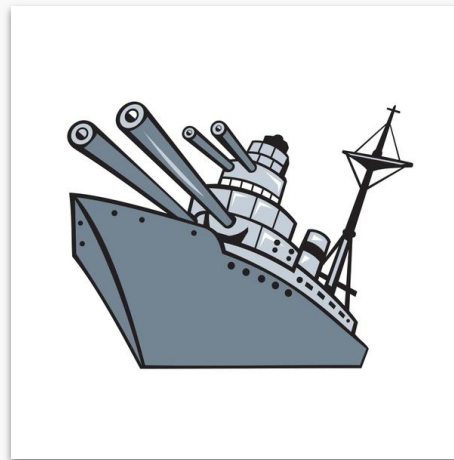
- Guess in Clusters or in Rows based on hits/misses
- Keep track of opponents previous guesses to place ships next time
- Query LLM for next move?
 - How good is ChatGPT at War Games...



Let the games begin!



- To enter the tournament
 - Share the agent with Globus Groups
 - Register your agent (code below)
- Rules
 - Round-Robin Tournament
 - 0.25 Second Timeout on Moves (with communication)
 - 50 move limit on games



Battleship Tournament Entry Instructions

- Join the “Academy-SC-Tutorial” Globus Group
- Paste your agent into `solutions/05-battleship/enter\_tournament.py`
- Set environment variables and run:

```
source tournament.env  
python enter_tournament.py -n “Your Name”
```

- Sharing Agents on the Hosted Exchange

```
factory = HttpExchangeFactory(...)  
console = await factory.console()  
await console.share_agent(<agent_id>, <globus_group_id>)
```

Demo: Academy Model Context Protocol

11:30 – 11:45 am

Building LLM-powered agentic applications

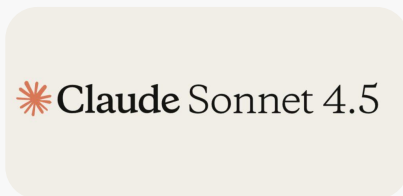
Popular LLMs (and their general availability dates)



June 17, 2025



August 7, 2025

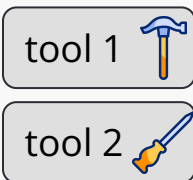


September 29, 2025



September 29, 2025

Model Context Protocol
(MCP)

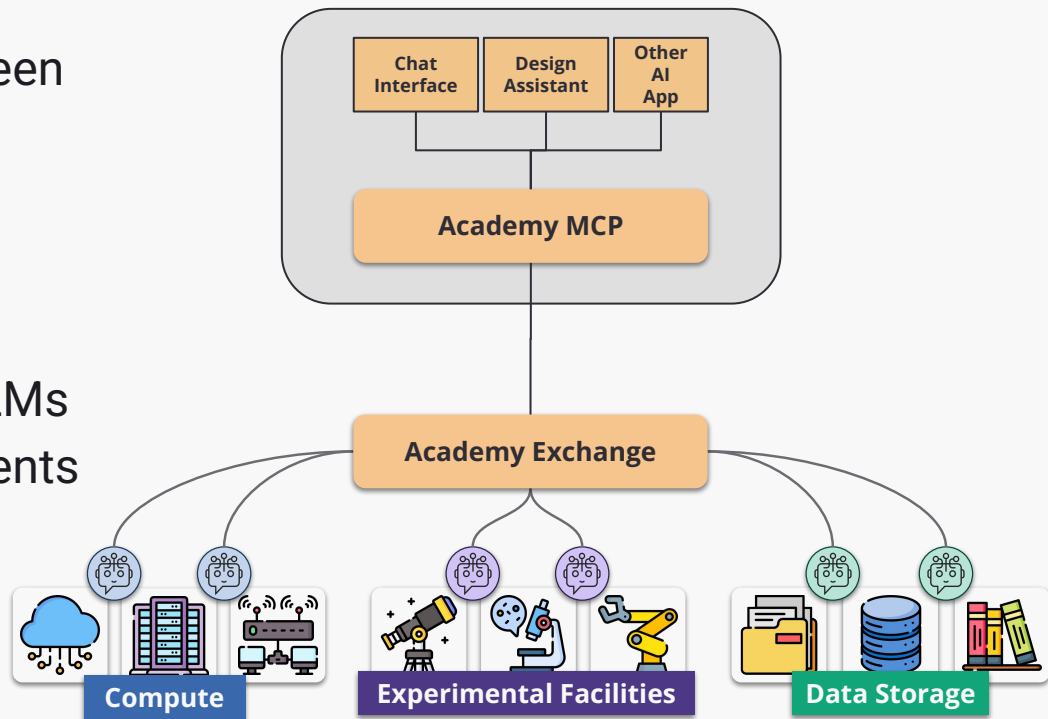


Outer world

MCP server

Academy-MCP Plug-in (Demo)

- Local MCP server bridges between Academy agents and AI applications
- Turn Academy agents into LLM **tools**
- Expose agentic **workflows** to LLMs
- Automatic **discovery** of new agents



Globus MCP servers

- Enable LLMs and agentic systems to manage data and computation across remote resources
 - Various transfer and compute capabilities supported with open Globus MCPs
 - Authentication via Globus client credentials



Tools:

- `submit_transfer_task()`
- `get_task_events()`
- ...



Tools:

- `list_my_endpoints()`
- `register_python_function()`
- `register_shell_command()`
- `submit_task()`
- `get_task_status()`

Wrap up

11:45 – 12:00 pm

What's Next for Academy?

- Community and Governance
 - Build an engaged, cross-disciplinary community of researchers and developers
 - Establish a sustainable governance and contribution model
- Scientific Engagement
 - Collaborate with domain science teams to evaluate efficacy, identify challenges, and uncover new opportunities for agents in practice
- Ecosystem Integration
 - Connect with the broader agent, AI, and scientific cyberinfrastructure ecosystem
- Technical Directions
 - Develop a secure, scalable, and robust managed exchange for the agent community
 - Enable integrated tool-calling and remote application execution
 - Strengthen provenance, auditability, and reproducibility across agentic workflows

Discussion

- How are you currently using (or planning to use) agents in your work or research infrastructure?
- What makes scientific and cyberinfrastructure contexts uniquely challenging or interesting for agentic systems?
- What are the key capabilities agents need to effectively support scientific workflows (e.g., reasoning, coordination, adaptation)?
- What challenges have you faced (or anticipate) in deploying, managing, or trusting agents across distributed systems?
- How can we promote interoperability and shared frameworks for agents across institutions and domains?
- What new opportunities could agentic systems enable for scientific discovery or collaboration?

Get Engaged



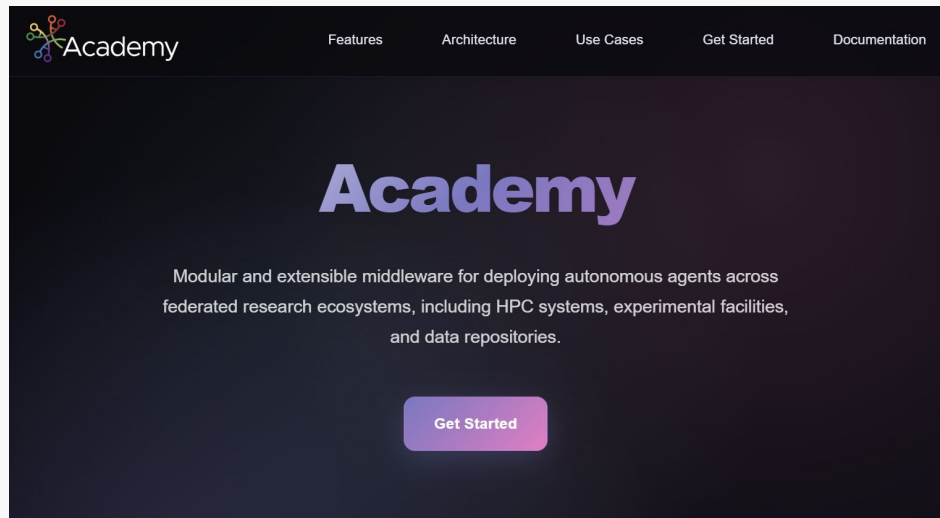
Try it out / star Academy on github / open issues / contribute to the open source project



Read the paper



Join the community / let us know how you are using Academy



Questions?



Thanks for attending!

Meet the Academy team



Greg
Pauloski



Alok
Kamatar



Yadu
Babuji



Ryan
Chard



Mansi
Sakarvadia



Ben
Clifford



Kyle
Chard



Ian
Foster

Learn More

- Website: academy-agents.org
- Docs: docs.academy-agents.org
- Paper: arxiv.org/abs/2505.05428v2

Reach Out



“Community” linked in website footer



github.com/academy-agents

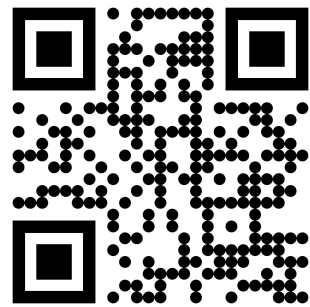


chard@uchicago.edu

Get Started

\$ pip install academy-py

academy-agents.org



THE UNIVERSITY OF
CHICAGO

globus  labs