

Title: EAIRA: Establishing a methodology to evaluate LLMs as research assistants.

Speakers: Frank Cappello

Collection/Series: Theory + AI Symposium

Date: April 08, 2025 - 9:10 AM

URL: <https://pirsa.org/25040059>

Abstract:

Recent advancements have positioned Large Language Models (LLMs) as transformative tools for scientific research, capable of addressing complex tasks that require reasoning, problem-solving, and decision-making. Their exceptional capabilities suggest their potential as scientific research assistants, but also highlight the need for holistic, rigorous, and domain-specific evaluation to assess effectiveness in real-world scientific applications. This talk describes a multifaceted methodology for Evaluating AI models as scientific Research Assistants (EAIRA) developed at Argonne National Laboratory.

This methodology incorporates four primary classes of evaluations. 1) Multiple Choice Questions to assess factual recall; 2) Open Response to evaluate advanced reasoning and problem-solving skills; 3) Lab-Style Experiments involving detailed analysis of capabilities as research assistants in controlled environments; and 4) Field-Style Experiments to capture researcher-LLM interactions at scale in a wide range of scientific domains and applications. These complementary methods enable a comprehensive analysis of LLM strengths and weaknesses with respect to their scientific knowledge, reasoning abilities, and adaptability. Recognizing the rapid pace of LLM advancements, we designed the methodology to evolve and adapt so as to ensure its continued relevance and applicability. This talk describes the current methodology's state. Although developed within a subset of scientific domains, the methodology is designed to be generalizable to a wide range of scientific domains.



EAIRA: Establishing a Methodology to Evaluate LLMs/rLLMs as Research Assistants (Progress)

Franck Cappello
and the AuroraGPT Evaluation Team
Argonne National Laboratory
<https://arxiv.org/abs/2502.20309>
or search EAIRA on Google

Large Languages Models (LLMs) Progress/4-5 years

Large Language Models (LLMs) have progressed drastically in the past 4-5 years (GPT3 released in 2020)

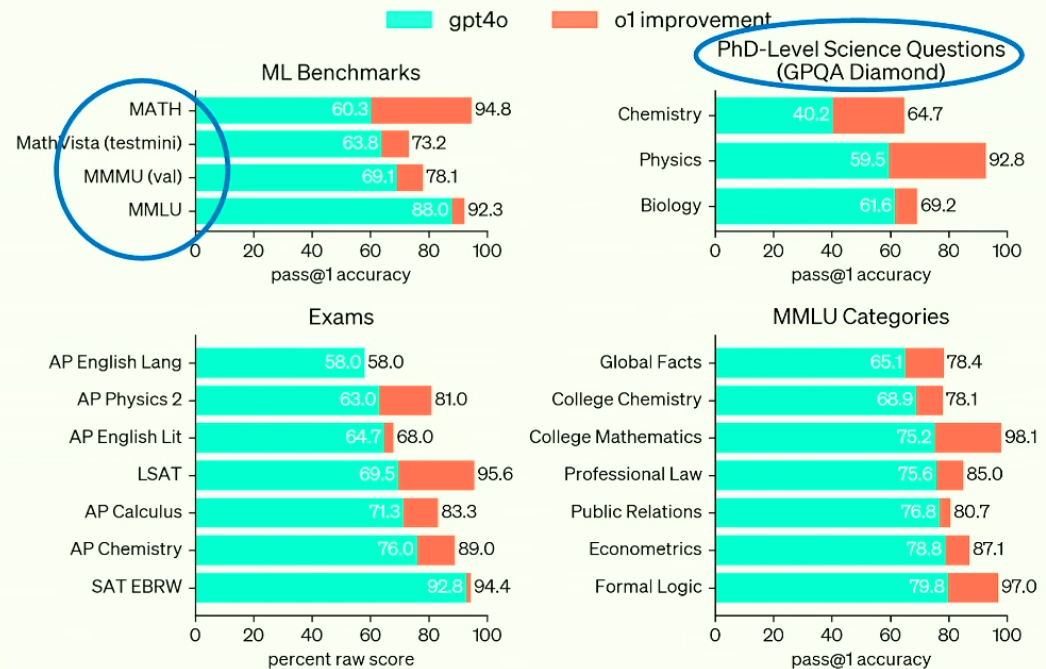
OpenAI's GPT4o (OpenAI 2024), Google's Gemini (Gemini 2024), and Anthropic's Claude (Anthropic 2024) are **excelling in text processing: summarization, information extraction, translation, and classification.**

Until recently (September 2024), Model performance (accuracy) progressed by increasing the size of the model and increasing the size of the training sets: **Trillions params/tokens**

On Sep. 12, 2024 OpenAI released **O1-preview: trained for reasoning**. Chain-of-thoughts + Reinforcement Learning during training. Internal chain-of-thoughts during inference.

→ **Greatly changed perception of what LLMs may be able to accomplish** in the near future.

Based on or adapted from classical test theory (CTT) in psychometrics



<https://sebastian-petrus.medium.com/openais-o1-mini-vs-o1-preview-a-comprehensive-comparison-b5d7b148dbda>

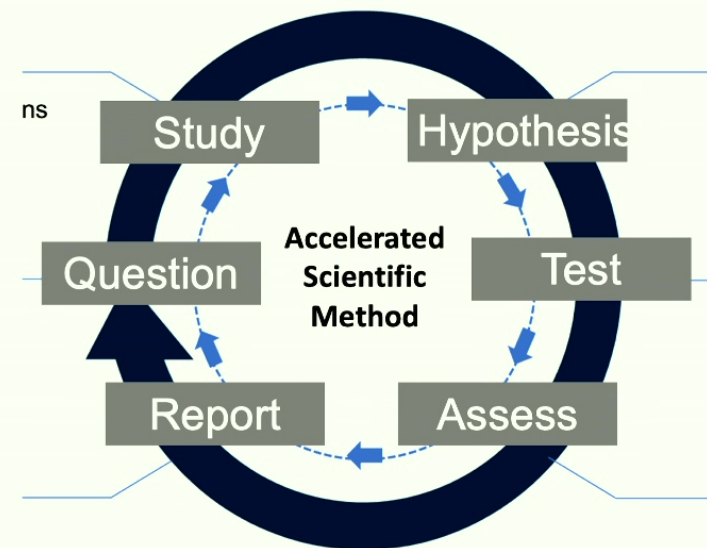
LLMs/rLLMs as Research Assistants?

Scientists assessed LLMs on **specific tasks**:

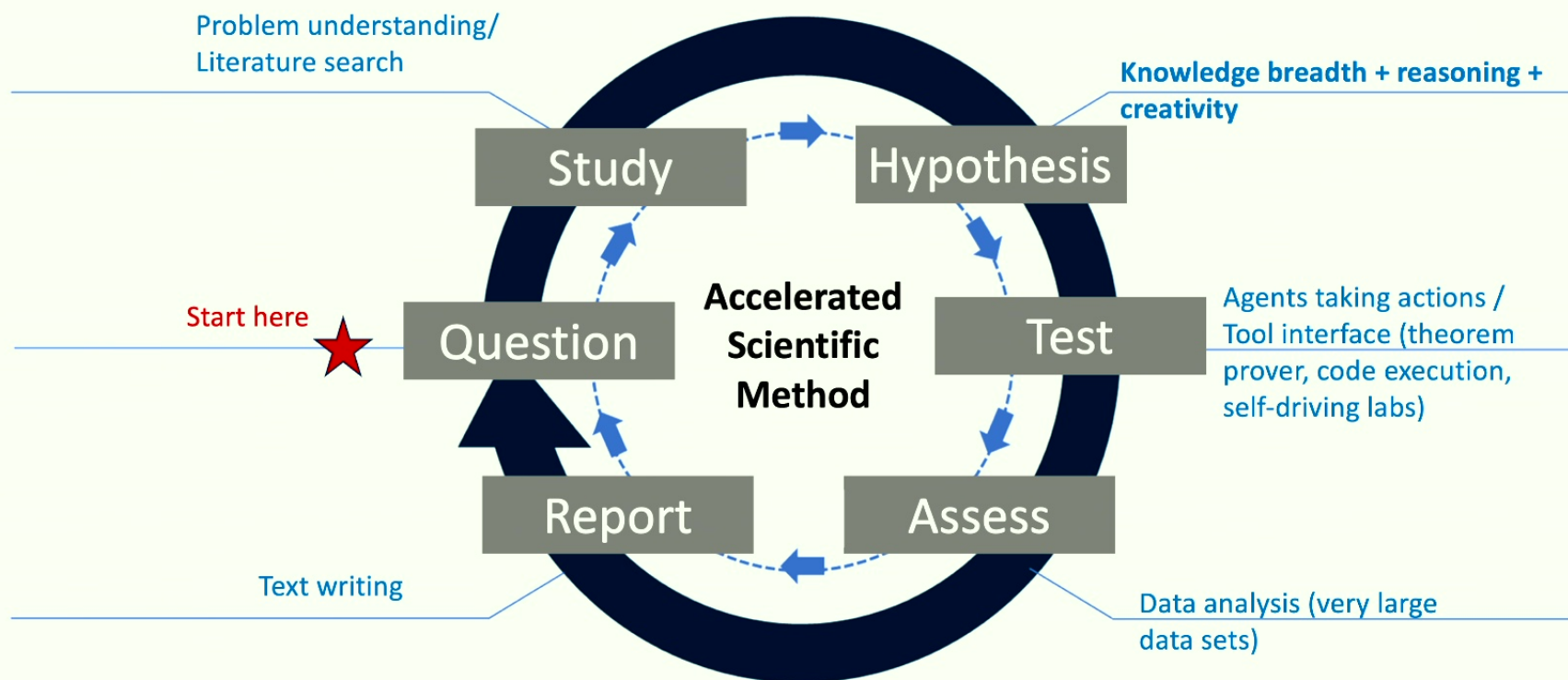
- Predicting molecular properties
- Uncovering genomic patterns
- Solving mathematical problems
- Creating and manipulating tools for simulations and analysis
- Etc.

→ Diversity and strength of skills and capabilities (Knowledge, Reasoning, Web search, Tools) **Suggest a new holistic approach** where LLMs/rLLMs are use as **scientific research assistants**

<https://doi.org/10.1038/s41524-022-00765-z>



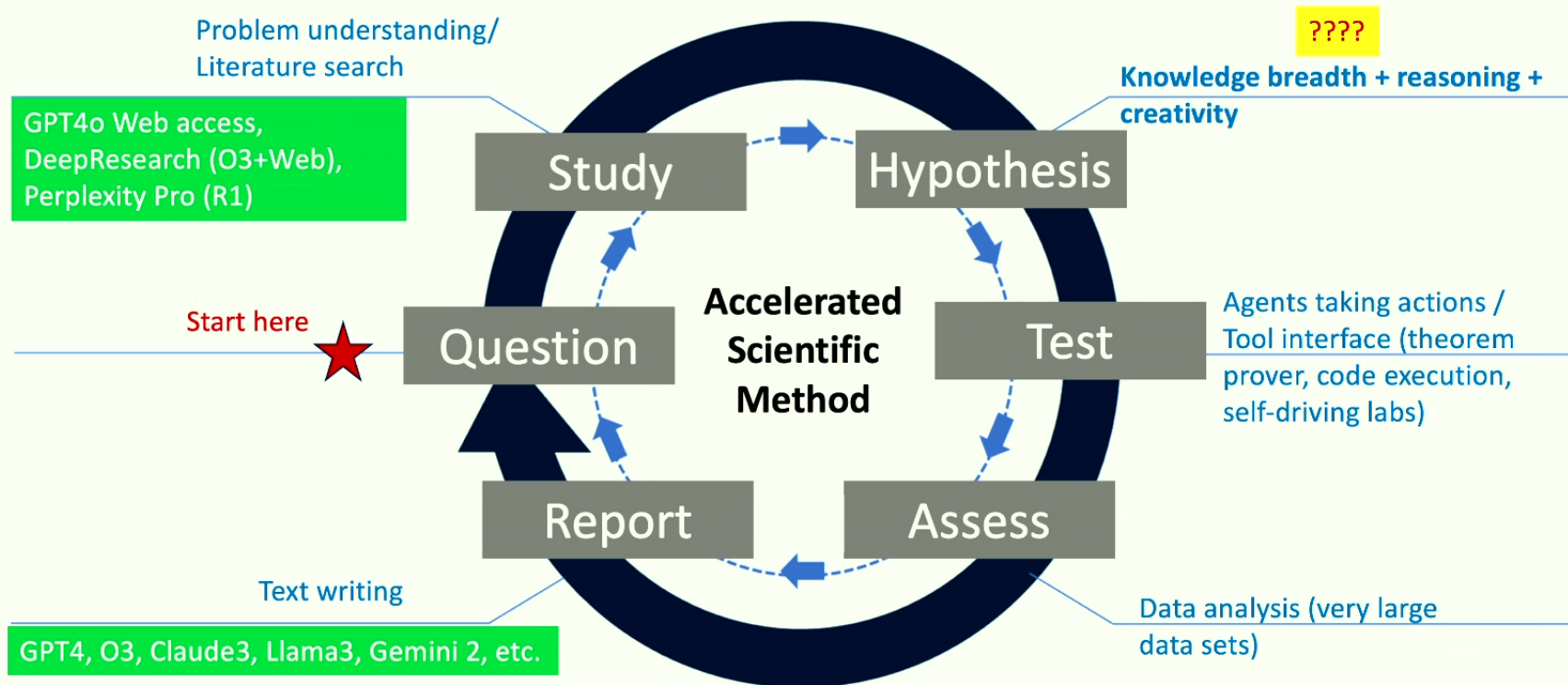
Accelerating Discovery using AI assistants (with OpenAI levels)



An ideal research will help in all these steps

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Characteristics of an “AI scientific assistant”

An AI-based system with:

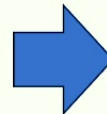
- **Scientific skills**
 - Reasoning, math, literature understanding, integrity
- **Effective assistance (no hallucination!, consistency in responses)**
 - **Correct** for all different tasks related to scientific activities
- **Relevant human and environment interaction modalities (communication skills)**
 - Understanding command (semantic of it), interface with tools and devices
- **Degree of autonomy**
 - From repeating learned workflows to developing the workflow.
 - **Capable of hypothesis generation**
- **Safe for the community**
 - Cannot be used to harm others: e.g. design harmful substances

2 Main Challenges Before Broader Adoption

1) Researchers need a way to **evaluate/compare the capabilities of LLMs in research context** for the different stages and tasks of the scientific research process **(which one is the best for what task?)**.

→ Guide the applications of LLMs and the integration with other tools,

→ Provides benchmarks for developers to improve their LLMs



2) As with other research tools and techniques, **researchers will adopt LLMs only if they trust their results** **(Can I, Should I trust this response?)**.

→ Need a way to assess the correctness of the produced results, in order to develop confidence in their use in scientific context.

A comprehensive,
Rigorous,
Accurate,
Transparent and
Community-approved
Evaluation methodology

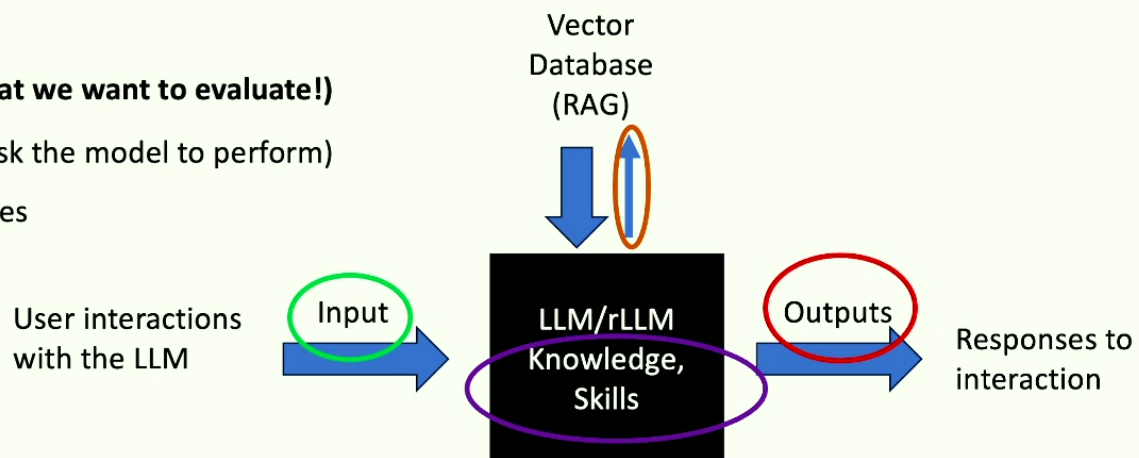
Evaluation Methodology

Goal of the evaluation: assess the knowledge and skills of LLMs/rLLMs

LLMs/rLLMs are so complex (number of layers, number of hidden dimensions, number of parameters, number of training tokens)

→ The community consider them as black boxes.

- Internal Skills and Knowledge (what we want to evaluate!)
- Capture interactions (what users ask the model to perform)
- Assess Requests to external modules
- Assess Response



→ LLM/rLLM Evaluation uses LLM/rLLM dialogic interface

Benchmarks: MCQs and Open Responses

- **Multi-Choice Questions (MCQs)**

- 1 correct response and 3, 4 or more distractors (wrong responses)
- **Difficulty:**
 - Generation is not trivial: distractors should not be easy to discard and not too close to the correct answer (risk of confusion)
 - Evaluation is trivial: just compare the model selection with correct response
- **Potential biases:**
 - E.g. Response ordering: → The model may choose the first answer more frequently

- **Open Responses:**

- 1 question. Model generates 1 response
- **Difficulty:**
 - Generation is trivial: generate a question relative to a domain
 - Evaluation is difficult: Require a human evaluation of the response
- **Potential biases:**
 - Room for interpretation: Human may score differently the same open response → scoring requires several human evaluation (consensus)

MCQ: GPQA: A Graduate-Level Q&A Benchmark (multi-domain)

- Scalable oversight research: Questions near the frontier of human expertise. Experts reach 65% (only!!)
- Generated manually 480 MCQs (4 possible answers): Molecular Biology (85), Genetics (20), Quantum Mechanics (64), High-Energy Particle Physics (46), Physics (43), Astrophysics (42), Electromagnetism and Photonics (12), Relativistic Mechanics (11), Statistical Mechanics (4), Condensed Matter Physics (4), Optics and Acoustics (1), Chemistry: Organic Chemistry (144), Chemistry (64), Inorganic Chemistry (3), Analytical Chemistry (2), Physical Chemistry (1)
- Methods for question generation:
 - From contractors (Ph. D. or in Ph. D. program).
 - Hired contractors from Upwork <https://www.upwork.com/> (question: are they real experts? Also Bias)
 - Contractors were paid + the majority of payment comes from bonuses conditional on the quality of their work. Between \$95 to \$150 per hour.
 - Instructed question writers to write difficult questions in their domain of expertise that other experts in the domain will be able to answer correctly, but that non-experts cannot answer even with the internet
- MCQ examples:

GPQA: A Graduate-Level Google-Proof Q&A Benchmark, David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, Samuel R. Bowman, <https://arxiv.org/abs/2311.12022>

Astrophysics

Astronomers are studying a star with a T_{eff} of approximately 6000 K. They are interested in spectroscopically determining the surface gravity of the star using spectral lines ($EW < 100 \text{ m\AA}$) of two chemical elements, E1 and E2. Given the atmospheric temperature of the star, E1 is mostly in the neutral phase, while E2 is mostly ionized. Which lines are the most sensitive to surface gravity for the astronomers to consider?

- A) E2 I (neutral)
- B) E1 II (singly ionized)
- C) E2 II (singly ionized)
- D) E1 I (neutral)

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- **O3: 87.3% accuracy on GPQA diamond***
→ O3 exceeds human scholars on this benchmark (**81%**)
→ **the benchmark is saturated**
! GPQA miss many domains (Climate, Computer Science, Biology, etc.)
!! **High Risk of Contamination**
*Diamond: (1) 2 out of 2 expert validators agree, (2) ≤ 1 out of 3 non-expert validators answers correctly
- Instructed question writers to write difficult questions in their domain of expertise that other experts in the domain will be able to answer correctly, but that non-experts cannot answer even with the internet
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Gap Analysis

- **MCQ Benchmarks:**

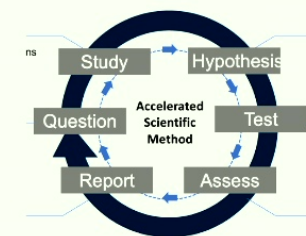
- Very few efforts are science-domain focused and validated + **only few domains represented**
- As the capabilities of LLMs/rLLMs improve → need to generate more difficult questions
 - **We need to automate the generation/validation and progressively increase difficulty**

- **Open response Benchmarks:**

- Very few efforts are science-domain focused and validated
- Evaluating is inherently challenging for domains that are unstructured by nature: e.g. Bio
 - **When possible → automate verification comparing codes, numerical results, math derivations**
 - **Else, explore automate response verification using LLM(s) as judge(s)**

- **Missing evaluation technique in real context:**

- Benchmarks do not reflect the actual complexity, diversity, level of details of real-world interactions between researchers and LLMs/rLLMs
 - **We need new techniques**



AuroraGPT*:

- **General purpose scientific LLM** – broadly trained – general corpora plus scientific papers and texts and structure science data
- **SAFE:** Trustworthiness, Safety, Security, Robustness, Privacy, Machine Ethics
- **Explore pathways** towards a “Scientific Assistant” model
- **Build with international partners** (RIKEN, BSC, others)
- **Multilingual** – English, 日本語, Français, Deutsche, Español, Italiana
- **Multimodal** – images, tables, equations, proofs, time-series, graphs, fields, sequences, etc.

*named after the Leadership Class Supercomputer at Argonne that will be used for much of the training

Aurora is:
166 Racks
10,624 Nodes
21,248 CPUs
63,744 GPUs
84,992 NICs
8 PB HBM
10 PB DDR5c



Groups:

- 01 Planning
- 02 Data
- 03 Model training (pre-training)
- **04 Evaluation (skills, trustworthiness, safety)**
- 05 Post-training (fine tuning, alignment)
- 06 Inference (on Aurora)
- 07 Distribution
- 08 Communication

Evaluation Methodology: What to measure

What to measure:

- **Knowledge Extraction, Retrieval, Distillation, Synthesis** : LLM is provided with a question and a truthful answer is expected
- **Text grounded**: Answer is expected fully grounded on peer reviewed references to support response.
- **Reasoning**: LLM is expected to solve deductive (Prove a theory or hypothesis from formal logic and observations), inductive (validate/explain observations from theories) problems
- **Creativity**: A creative answer is expected from a question or instruction: e.g. find a solution to open scientific questions.
- **Thoughtful dialogue, Coding, etc.**
- **safety, usability, robustness (adversarial attacks), cost/energy (training, inference)**

Criteria for all of the above:

- **Correctness** (of facts, results),
- **Accuracy** of solutions AND reasoning,
- **Reliability** (consistently good in quality or performance),
- **Speed** (how fast to produce a response), O1-pro can take minutes to respond to a single prompt
- **Consistency** (slight prompt variations should not generate significantly different responses),
- **#shots** (how many examples are needed for good quality),
- **Extent of Prompt Engineering**.

Challenges:

- **AI model capabilities (knowledge, reasoning, correctness) are increasing at extreme pace**
- **Evaluation should be done in enclaves** (AI models should not be trained on the tests)
- **Generation and validation of large corpus** of difficult enough tests

Multi-faceted Methodology

End-to-End

| Proposed Methodology | | | | |
|-----------------------|---|--|--|--|
| Techniques | MCQ Benchmarks | Open Response Benchmarks | Lab Style Experiments | In the Wild Field Style Experiments |
| Main Goal | Testing knowledge breadth, basic reasoning | Testing knowledge depth, planning, reasoning | Realistic testing | Realistic trend analysis and weakness diagnosis |
| Problem Type | Predetermined , Fixed Q&As with known solutions | Predetermined , Fixed Free-Response Problems with known solutions | Individual Human Defined Problems with unknown solutions | Many Human Defined Problems with (un)known solutions |
| Verification | Automatic response verification | Automatic or Human response verification | Humans detailed response analysis | Scalable automatic summary of human response |
| Examples | Astro, Climate, AI4S (multi-domain), Existing Benchmarks | SciCode, ALDbench | see "lab style experiments" | see "field style experiments" |
| Cross Cutting Aspects | ← Trust and Safety (ChemRisk), Uncertainty Quantification, Scalable Software Infrastructure (STAR) → | | | |

Methodology consisting of **4 complementary evaluation techniques** to comprehensively assess the capabilities of LLMs as scientific assistants:

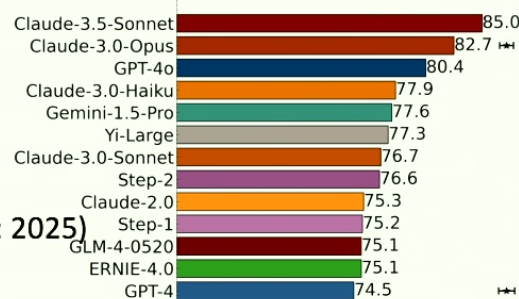
- **purple text** shows prior contributions by the researchers participating in AuroraGPT
- **blue text** shows AuroraGPT contributions.
- Black text aspects adapted from existing work are included for a complete approach.

ASTRO MCQ Benchmark

- **4425 Automatically generated MCQs**
- From 885 articles in [Annual Review of Astronomy and Astrophysics](#), 1963 to 2023.
- Instructed Gemini-1.5-Pro to propose 5 questions that can be answered based on the paper's content.
- Each question was accompanied by four options (A, B, C, D) only one of which is correct.
- Robustness considerations added to the prompt generating the questions.
- **200 MCQs were manually validated**

Some take aways:

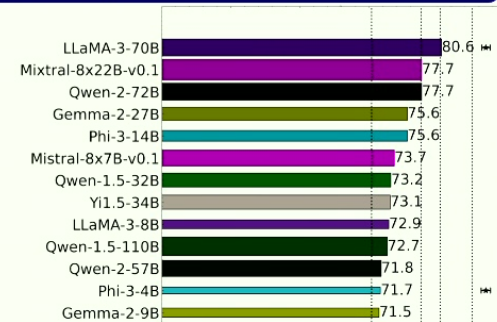
- Claude 3.5 Sonnet best (no O1 test)
- Llama-3-70B on par with GPT4o
- Published in July 2024 on arXiv (journal: 2025)
- **Benchmark almost/probably saturated**



Sample question from Astronomy benchmark dataset

How does the presence of stellar companions influence the formation and detection of exoplanets?

- (A) Stellar companions can dilute transit signals, potentially leading to misclassification of planets and inaccurate parameter estimations. Additionally, their gravitational influence can suppress planet formation in close binary systems.
- (B) Stellar companions provide additional sources of gravitational perturbations, enhancing planet formation by promoting planetesimal accretion and facilitating the formation of gas giants.
- (C) Stellar companions contribute to the metallicity enrichment of planetary systems, leading to the formation of more massive and diverse planets, including super-Earths and hot Jupiters.
- (D) Stellar companions act as gravitational lenses, increasing the detectability of exoplanets through microlensing events and enabling the discovery of planets at greater distances from their host stars.



Y.-S. Ting, et al.i, AstroMLab 1: Who wins astronomy jeopardy!
Astronomy and Computing, Volume 51, 2025,



AI4S MCQ Benchmark: Motivations

AI4S benchmark: evaluate knowledge extension of LLMs in many scientific domains.

GPQA has only 448 MCQs → AI4S objective: **generate thousands MCQs**

→ continuously add new more difficult MCQs as LLMs and LRMs progress in their capabilities.

The **current MCQ benchmarks, including GPQA, are static**:

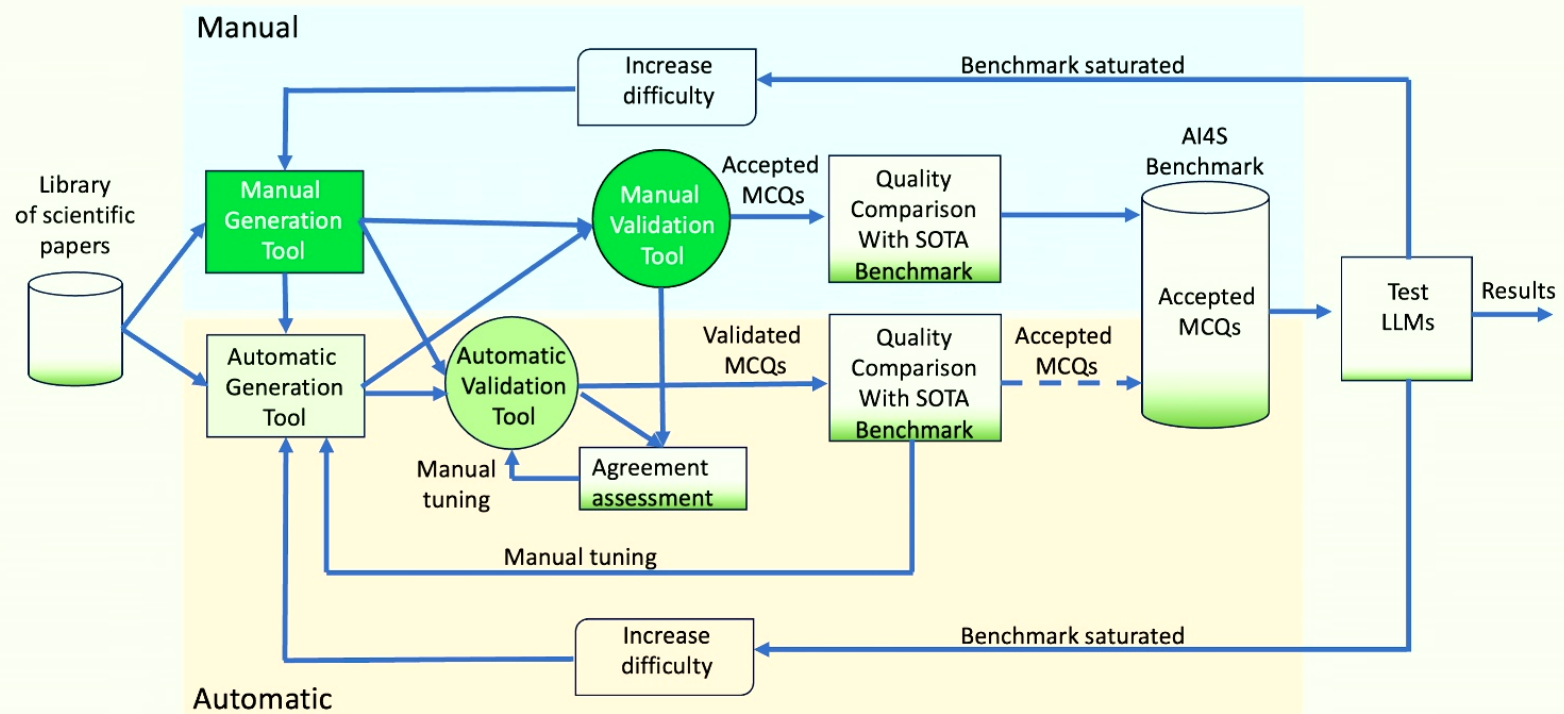
1) they are **quickly saturated** because of the fast progress of LLMs and LRMs.

2) there is a **high risk of contamination** (benchmark included in the training sets)

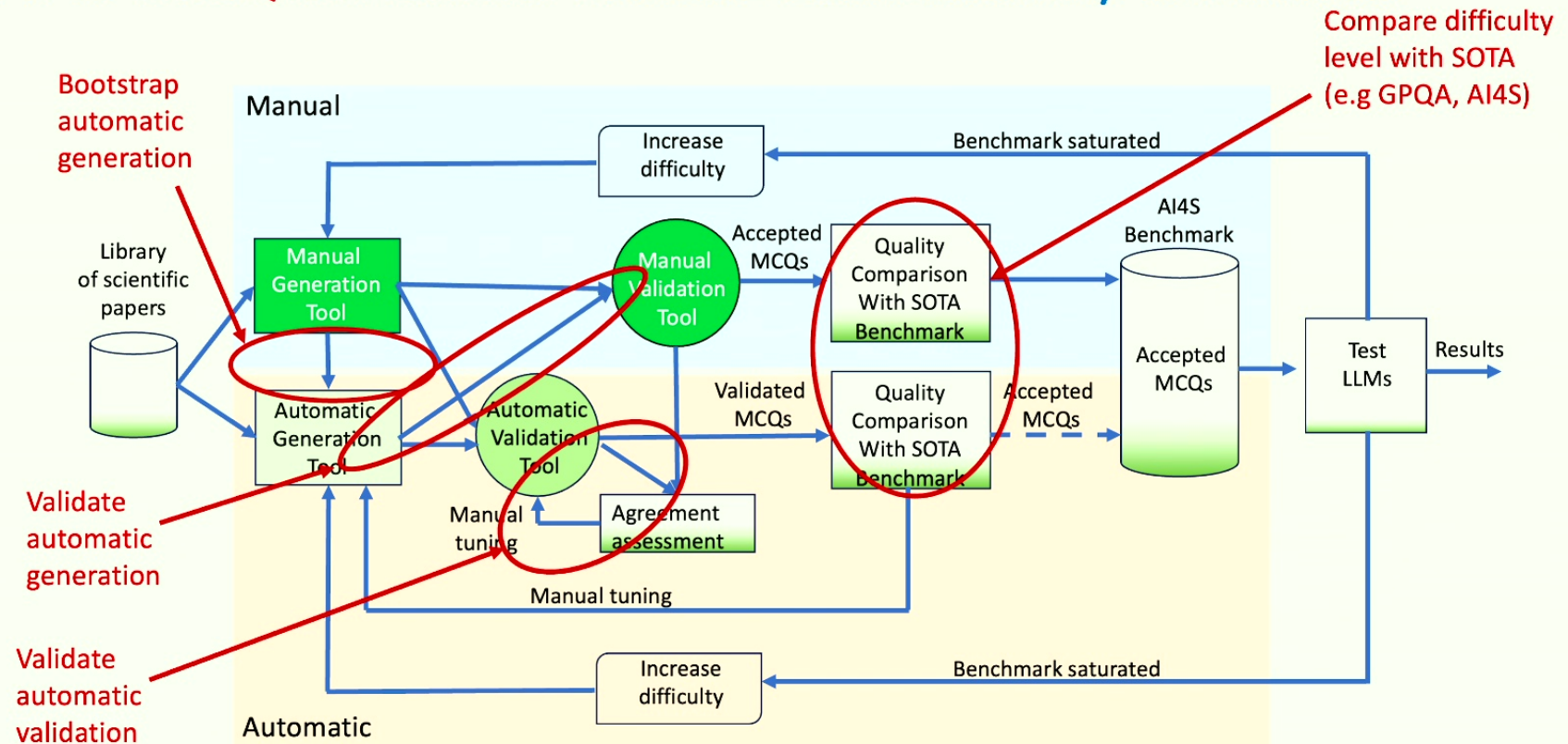
→ AI4S novel approach: Automatic continuous Generation and validation of Increasingly Large MCQ benchmarks: **AGIL**

- Need to bootstrap automatic generation (compare automatic versus human generation)
- Need to validate automatic generation (acceptance rate, level of difficulty)
- Need to validate the automatic validator!
- Need to compare MCQ level of difficulty with GPQA (and other benchmarks)

AI4S MCQ Benchmark: AGIL Generation/Validation

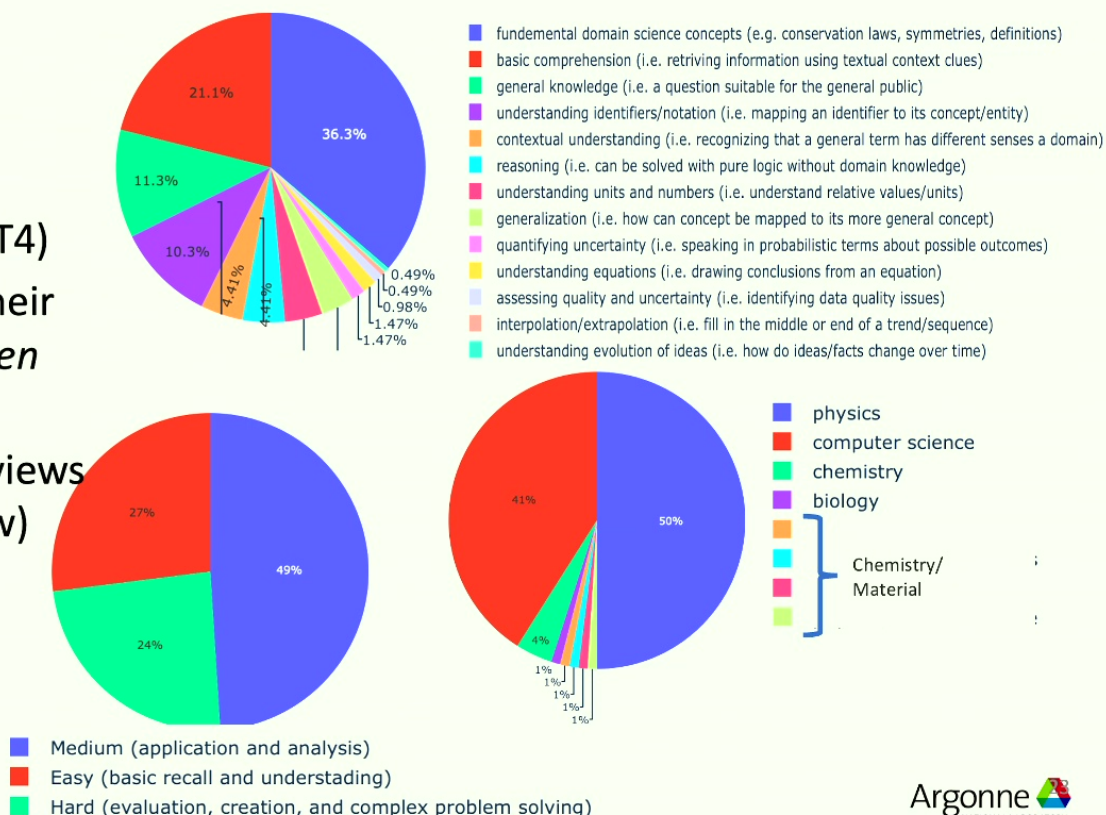


AI4S MCQ Benchmark: AGIL Generation/Validation



AI4S MCQ Benchmark: 1000 MCQs (254 accepted)

- MCQ generated from papers
- **980** generated MCQs
 - 720 manually
 - 260 automatically (with GPT4)
- Volunteer participants tested their MCQs on local *Llama 3* and *Qwen* before submission
- 588 volunteer manual MCQ reviews (similar process as paper review)
- 317 MCQs validated so far
- **254 accepted (manually)**
- 317-254 → irrelevant MCQs



AI4S MCQ Benchmark: Difficulty Evaluation

Difficulty of the AI4S MCQs compared to GPQA MCQs

5 shots

GPQA: 1 correct, 3 distractors. Random choice: 25%

ANL AI4S: 1 correct, 4 distractors. Random choice: 20%

GPQA Diamond – 198 MCQs (2/2 experts agree & $\leq 1/3$ non-experts correct)

<https://huggingface.co/spaces/wenhu/Science-Leaderboard>

| Model (CoT) | ▲ Avg | ▲ TheoremQA | ▲ MATH | ▲ GSM | ▲ GPQA | ▲ MMLU-STEM | ▲ |
|----------------------|-------|-------------|--------|-------|--------|-------------|---|
| GPT-4-turbo-0409 | 67 | 48.4 | 69.2 | 94.5 | 46.2 | 76.5 | |
| LLaMA-3-70B-instruct | 61.9 | 42 | 47.4 | 92 | 48.9 | 79 | |

| | | | ANL AI4S |
|-------------|----------|-----------------------------|-------------------------|
| Llama-3-8B | accepted | 254 0.2008 (± 0.0252) | 0.2717 (± 0.0280) |
| Llama-3-70B | accepted | 254 0.2598 (± 0.0276) | 0.3701 (± 0.0304) |

- AI4S accepted overall more difficult (37% correct) than GPQA Diamond (49% correct).
- AI4S is 41% more difficult (excess accuracy) or 12% more difficulty (excess accuracy relative to random)
- Among 254 MCQs, 71 were tagged AI (generated with LLM). Same accepted %.

SciCode (integrated into the methodology) Open Response Benchmark

Scientist-curated coding benchmark (mathematics, physics, chemistry, biology, and materials science)

80 main problems (numerical methods, simulation of systems),
decomposed into 338 subproblems.

The problems naturally factorize into multiple subproblems, **each involving knowledge recall, reasoning, code synthesis.**

To solve a main problem, LLMs must implement multiple Python functions for to each subproblem and integrate them into a comprehensive solution.

SciCode provides gold-standard solutions and multiple test cases for reliable automatic evaluation.

Problems are very challenging: inspired from Nobel price level problems.

| | |
|---|---|
| <p>Main Problem</p> <p>Question: Generate an array of Chern numbers for the Haldane model on a hexagonal lattice by sweeping the following parameters: [MORE QUESTION TEXT]</p> <p>Docstrings</p> <pre>def compute_chern_number_grid(delta, a, t1, t2, N): """ Args: delta (float): The grid size in kx and ky axis. [MORE ARGUMENTS] Returns: results (ndarray): 2D array of shape(N, N), the Chern numbers. [MORE RETURN VALUES] """</pre> <p>Dependencies</p> <pre>import numpy as np import cmath from math import pi, sin, cos, sqrt</pre> | <p>Subproblem 2</p> <p>Background: Source: [CITATION] Here we can discretize the two-dimensional Brillouin zone into grids with step [MORE BACKGROUND TEXT]</p> <p>Question: Calculate the Chern number using the Haldane Hamiltonian.</p> <p>Docstrings</p> <pre>def compute_chern_number(delta, a, t1, t2, phi, m): """ Function to compute the Chern number. Args: delta (float): The grid size in kx and ky axis. [MORE ARGUMENTS] Returns: chern_number (float): The Chern number. """</pre> |
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Minyang Tian, SciCode: A Research Coding Benchmark Curated by Scientists, arXiv:

[arXiv:2407.13168](https://arxiv.org/abs/2407.13168)



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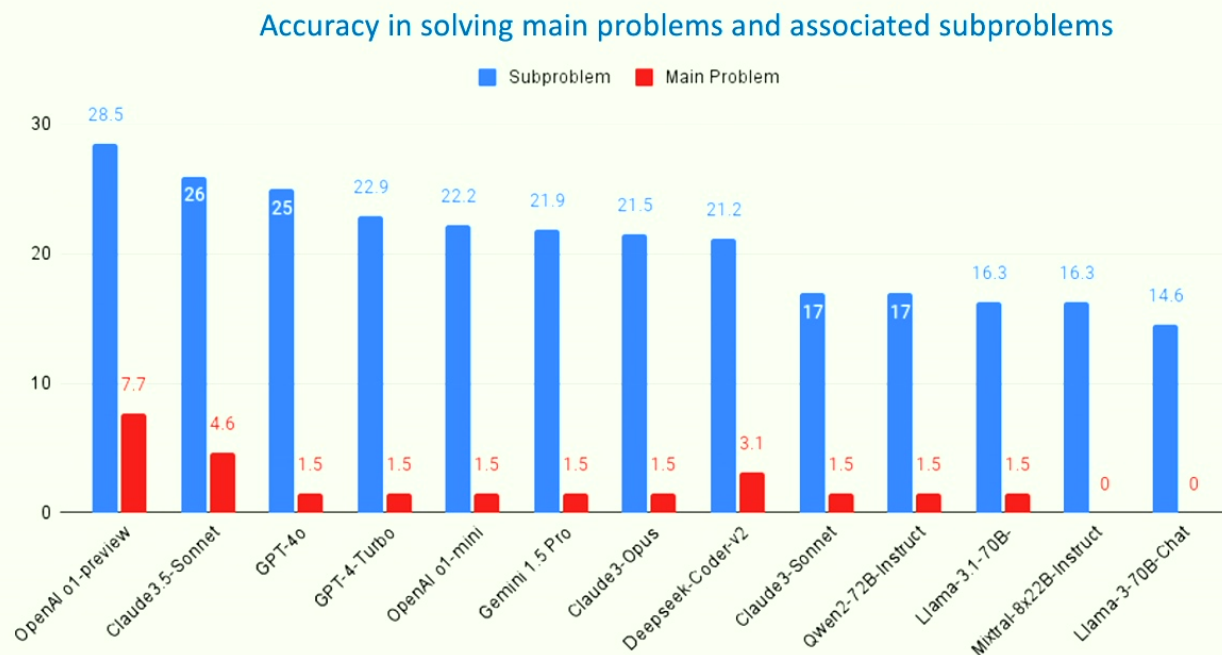
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SciCode (integrated into the methodology) Open Response Benchmark

OpenAI o1-preview can only solve 7.7% of main problems.



Demonstrate that even the best models are cannot solve difficult problems.

Lab-Style Experiment: End-to-End Evaluation

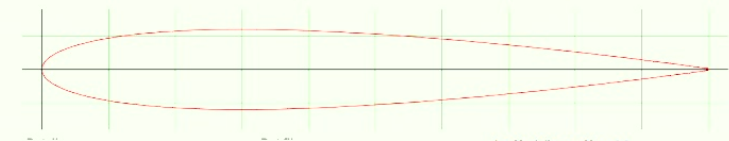
- Ran 5 experiments to observe the “distance” between an ideal assistant and Existing LLMs (Large Languages Models)
- Experiments related to:
 - DAG Scheduling
 - PDE Solving
 - **0 overhead checkpointing for LLMs training (HPDC24 Best Paper)**
 - Quantum entanglement
 - Life at temperature beyond known limits: e.g. 150°C
- Experiments >25 hours (~6h per experiment), >125 prompts
- Tested Models: O1, Argo/O1, ChatGPT4o, GPT3.5, Gemini 2, Gemini 1.5, Claude3 Sonnet/Haiku, Mistral, Llama3 (70b, 405B), Perplexity Pro, (not all models were tested on all prompts)

Example: PDE Solving Problem

Transonic flow passing over an airfoil

NACA 0012 AIRFOILS - NACA 0012 airfoil

Mach Number Contours



The given equation is:

$$(A(x)\rho(u)\phi_x)_x = 0$$

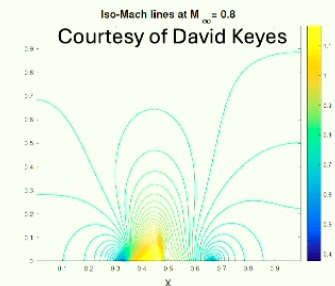
with boundary conditions:

$$\phi(0) = 0 \quad \text{and} \quad \phi(2) = \phi_R = 1.15$$

where:

$$\begin{aligned} u(x) &= \phi_x(x) \\ A(x) &= 0.4 + 0.6(x-1)^2 \\ \rho(u) &= \left(1 + \frac{\gamma-1}{2}(1-u^2)\right)^{\frac{1}{\gamma-1}} \end{aligned}$$

and $\gamma = 1.4$.



L. Liu, F.-N. Hwang, L. Luo, X.-C. Cai, D. E. Keyes, A Nonlinear Elimination Preconditioned Inexact Newton Algorithm, SIAM Journal on Scientific Computing, Vol. 44, Iss. 3 (2022)10.1137/21M1416138

Collaboration with David Keyes, KAUST

Context: Our goal is to solve a 1-dimensional nonlinear second-order boundary value problem for $\phi(x)$.

$\phi(x)$ is a velocity potential, the velocity u is the x -derivative of $\phi(x)$, denoted $u(x)=\phi_x(x)$.

We define two auxiliary functions, $A(x) = 0.4 + 0.6(x-1)^2$, the cross-section of a windtunnel, and the local density, $\rho(u) = (1 + (\gamma-1)(1-u^2)/2)^{1/(\gamma-1)}$.

The equation is $(A(x)\rho(u)\phi_x)_x = 0$ with left boundary condition $\phi(0)=0$ and right boundary condition $\phi(2)=\phi_R$.
 $\phi_R=1.15$, $\gamma=1.4$

Asked 9 different prompts covering:

- Problem attack:** How you would solve this problem, describe important steps?
- Clarification:** we gave the boundary values because one model got them wrong
- Solution steering:** asked specifically to use upwinding approach (none of the model proposed this independently)
- Approach to avoid oscillation:** solution steering did not work: "what method should one use to avoid oscillations". Only Llama 3 proposed upwinding
- Code generation instructing upwinding* (Llama 3 and GPT4o only):** Generate code using upwind differencing for ϕ .
- Code generation with library (PETSc):** Write a code solving the problem using Petsc and your upwinding scheme (Only Llama 3).
- Code generation correction 1:** "You gave a solution using a linear solver for a non-linear problem. Please use a non-linear solver."
- Code generation correction 2:** "Please write the residual and Jacobian functions."
- Code generation correction 3:** "The Jacobian function was not complete. Please write it again."



Upwinding aims to improve the accuracy and stability of numerical solutions by considering the direction of this information propagation

Lab Style Experiments: PDE Solving: Results

Score (**subjective**): A to F, Scientist + Google: A (reference)

Problem attack strategy (initial | clarification):

Claude3, Llama3

GPT4o

GPT3.5

C (did not recognize the need to upwind)

D (proposed shooting method would not work: did not consider the shock)

F | C (did not compute correctly the boundary values)

Solution steering :

Llama3

GPT4o

Claude 3

GPT4 turbo

B (pointed in good directions)

D (extra instruction to avoid oscillations did not change its approach)

D (did not recognize how to solve this problem)

F (propose to go to higher order. This will make the problem worse)

Approach to avoiding oscillation:

Llama3

Claude 3

GPT4o

GPT3.5

A (“provide 8 value approaches, including the one I would use”)

C (wrote an explicit upwinding formula for phi instead of density)

D (proposed 3 more directions without details: too vague)

E (proposed many textbook solution. But not the correct one: upwinding)

Code generation for upwinding/correction:

Llama3

GPT4o

C (needed a lot of corrections to generate all the codes)

E (generated upwinding code for phi instead of density not clear how this would work in terms of accuracy or oscillation stability)

Field Style Experiment: End-to-End Eval

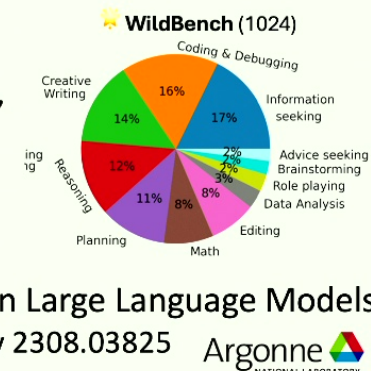


Lab style experiments: Human evaluation, tries to solve 1 specific problem, compare different models, guide LLMs (requires efforts: some prompt engineering),

Field style experiments: Automatic evaluation, capture what researchers actually ask, much broader diversity of Q&As, large diversity of prompt engineering, statistical evaluation

Several papers on this topic (but not for Science activity)

- **WildBench**: Benchmarking LLMs with Challenging Tasks from Real Users in the Wild, B. Y. Lin and Y. Deng and K. Chandu and F. Brahman and A. Ravichander and V. Pyatkin and N. Dziri and R. Le Bras and Y. Choi, 2024, arXiv 2406.04770
- **HaluEval-Wild**: Evaluating Hallucinations of Language Models in the Wild, Zhiying Zhu and Yiming Yang and Zhiqing Sun, 2024, arXiv, 2403.04307
- **"Do Anything Now"**: Characterizing and Evaluating In-The-Wild Jailbreak Prompts on Large Language Models Xinyue Shen and Zeyuan Chen and Michael Backes and Yun Shen and Yang Zhang, 2024, arXiv 2308.03825



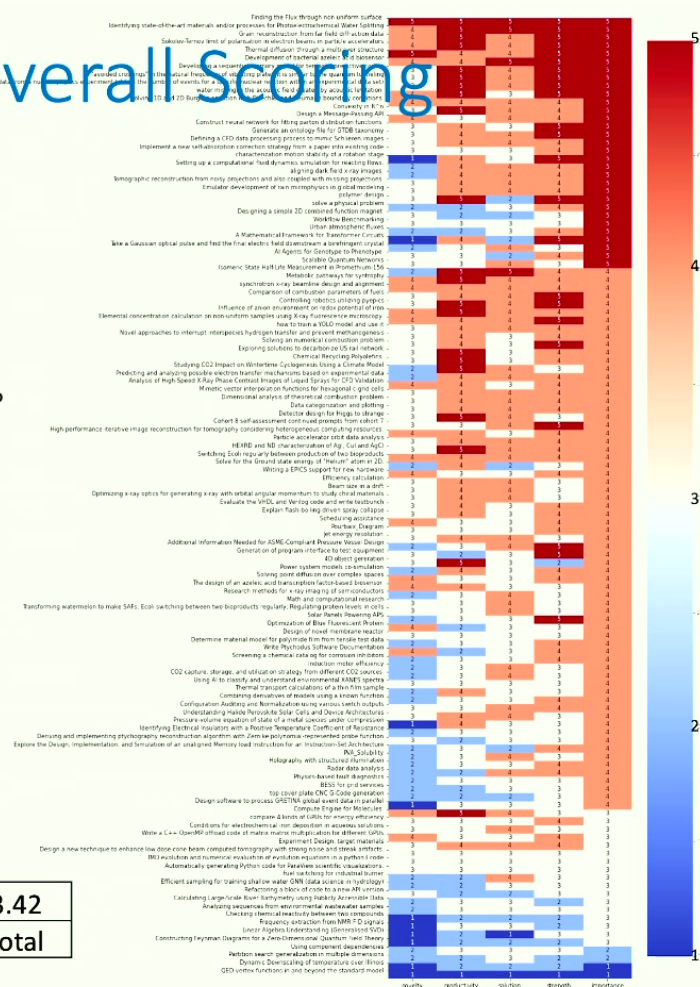
Field Style Experiment: AJS: Overall Scoring

Argonne researcher contributions on a voluntary basis.

- **Novelty 21%** are notably novel or groundbreaking
 - Based on the performance on this problem, How innovative do you expect the responses to be from the model?
- **Productivity 51%** compare these models to PhD students or postdocs
 - Based on the models performance on this problem, I would expect the productivity and effectiveness of this model to be comparative to the ideal?
- **Solution 50%** are exceptional or strong solutions
 - Based on the model's performance, how complete, correct, or plausible do expect solutions to be from the proposed solution?
- **Strength: 59%** are significantly or noticeably improving productivity
 - Based on the model's performance on this problem, how much would you expect the model to impact you or your team's productivity?
- **Importance: 82%** are very important or critical to the team's success
 - Based on the model's performance today, How much of a comparative advantage do you expect it be to have readily available access to this tool?

Averages:

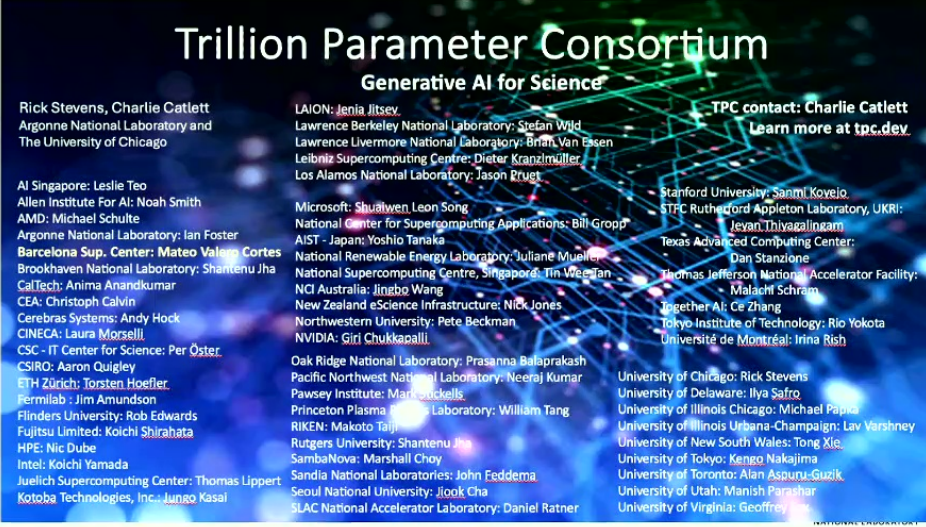
| | | | | | | |
|---------------------|------------|--------------|----------|---------|----------|-------|
| 3.695 | 3.99 | 3.41 | 3.61 | 2.79 | 3.33 | 3.42 |
| Expected difficulty | importance | productivity | strength | novelty | solution | total |



What's next

- Continue **Benchmarks development** (skills, trustworthiness, safety)
- **More Lab-style experiments** / improve the method
- **More Field-style experiments** / improve the method
- Develop **Frontier Science** (extremely difficult problems ~ FrontierMath)

- **May TPC Hackathon at Helsinki, May 6-8**



The poster for the Trillion Parameter Consortium (TPC) features a dark blue background with a glowing network of white and yellow lines connecting various nodes, symbolizing a global consortium. The title 'Trillion Parameter Consortium' is prominently displayed at the top in a large, white, sans-serif font, with the subtitle 'Generative AI for Science' below it in a smaller, yellow font. The poster lists numerous member institutions and their representatives, organized into three main columns. On the right side, there is a call to action: 'TPC contact: Charlie Catlett' and 'Learn more at tpc.dev'. The overall design is modern and tech-oriented, reflecting the cutting-edge nature of the consortium's work.

Trillion Parameter Consortium
Generative AI for Science

TPC contact: Charlie Catlett
Learn more at tpc.dev

Members:

- LAION: Jlenia Jitsev
- Lawrence Berkeley National Laboratory: Stefan Wild
- Lawrence Livermore National Laboratory: Brian Van Esen
- Leibniz Supercomputing Centre: Dieter Kranzlmueller
- Los Alamos National Laboratory: Jason Ruest
- Microsoft: Shualwen Leon Song
- National Center for Supercomputing Applications: Bill Gropp
- AIST - Japan: Yoshio Tanaka
- National Renewable Energy Laboratory: Julianne Mueller
- National Supercomputing Centre, Singapore: Tin Wee Tan
- NCI Australia: Jingbo Wang
- New Zealand eScience Infrastructure: Nick Jones
- Northwestern University: Pete Beckman
- NVIDIA: Giri Chukkappailli
- Oak Ridge National Laboratory: Prasanna Balaprakash
- Pacific Northwest National Laboratory: Neeraj Kumar
- Pawsey Institute: Mark Buckells
- Princeton Plasma Physics Laboratory: William Tang
- RIKEN: Makoto Tajima
- Rutgers University: Shantenu Jha
- SambaNova: Marshall Choy
- Sandia National Laboratories: John Feddema
- Seoul National University: Jiook Cha
- SLAC National Accelerator Laboratory: Daniel Ratner
- Stanford University: Sanmi Koyejo
- STFC Rutherford Appleton Laboratory, UKRI: Jeyan Thiyaazalingam
- Texas Advanced Computing Center: Dan Stanzione
- Thomas Jefferson National Accelerator Facility: Malachi Schram
- Together AI: Ce Zhang
- Tokyo Institute of Technology: Rio Yokota
- Université de Montréal: Irina Rish
- University of Chicago: Rick Stevens
- University of Delaware: Ilya Saeed
- University of Illinois Chicago: Michael Papadimitriou
- University of Illinois Urbana-Champaign: Lav Varshney
- University of New South Wales: Tong Xie
- University of Tokyo: Kengo Nakajima
- University of Toronto: Alan Aspuru-Guzik
- University of Utah: Manish Parashar
- University of Virginia: Geoffrey Gordon

Additional Members:

- Rick Stevens, Charlie Catlett
Argonne National Laboratory and
The University of Chicago
- AI Singapore: Leslie Teo
- Allen Institute For AI: Noah Smith
- AMD: Michael Schulte
- Argonne National Laboratory: Ian Foster
- Barcelona Sup. Center: Mateo Valero Cortes
- Brookhaven National Laboratory: Shantenu Jha
- CalTech: Anima Anandkumar
- CEA: Christoph Calvin
- Cerebras Systems: Andy Hock
- CINECA: Laura Morselli
- CSC - IT Center for Science: Per Oster
- CSIRO: Aaron Quigley
- ETH Zürich: Torsten Hoeftler
- Fermilab: Jim Amundson
- Flinders University: Rob Edwards
- Fujitsu Limited: Koichi Shirahata
- HPE: Nic Dube
- Intel: Koichi Yamada
- Juelich Supercomputing Center: Thomas Lippert
- Kotoba Technologies, Inc.: Junso Kasal

1,000 Scientists Jam Session

Feb. 28, 2025

Mix of Lab and Field
style experiments:

- 1 full day
- 10 labs
- 1500 researchers
- o1 pro/DeepResearch
- Claude 3.7 extended

Argonne:

720 problems
2500 prompts

Total:

2800+ problems
15000+ assessed prompt
responses

Next Jam with XAI, NVIDIA, Google
June?



Thanks!

Q&As

<https://arxiv.org/abs/2502.20309>

Or search **EAIRA** on Google

