

Position: Benchmarking is Broken – Don’t Let AI be its Own Judge

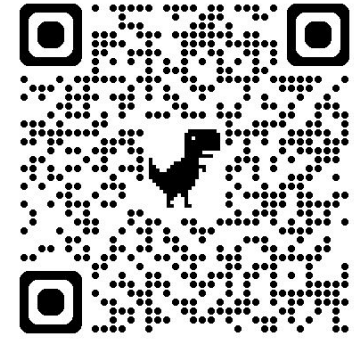
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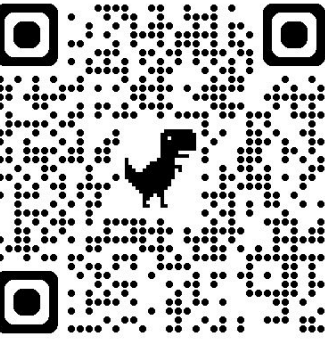
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PeerBench Platform



Paper

Motivation

Benchmarks shape AI progress, policy, and investment. But today’s evaluation ecosystem is noisy, fragmented, and easily gamed. We argue for a unified, live, and quality-controlled approach to restore signal and trust.

What’s Broken in Today’s Benchmarks?

A non-exhaustive summary of the flaws in today’s AI evaluation paradigm includes:

- Data Contamination:** Data leakage / injection into training corpora; **Memorization isn’t Generalization.** Public static datasets encourage hype-driven “state-of-the-art” claims.
- Cherry-picking & Selective Reporting:** Hype by showcasing only favorable slices (selective reporting); Collusion risks between benchmark creators and model/agent owners.
- Biased Test Data:** Ad-hoc curation can unfairly advantage or disadvantage specific models.
- Dataset Collection Undervaluation:** Dataset and benchmarking efforts are often treated as lower-status contributions; Inconsistent licensing and documentation complicate standardization efforts; Datasets are “reduced, reused, and recycled” without thorough contextualization.
- Noisy Metrics & Fragmentation:** Heterogeneous tokenizers, scoring rules, and ad-hoc evaluation scripts.
- Private Opacity:** Centralized control ≈ uncheckable claims; legitimacy via reputation rather than design.
- Lack of Proctoring & Fairness:** No identity checks, unlimited submissions, uneven access → gaming and bias.

Example 1: Llama 4 Overfitting Controversy

 r/LocalLLaMA • 24 days ago
myougi
“Serious issues in Llama 4 training. I Have Submitted My Resignation to GenAI”

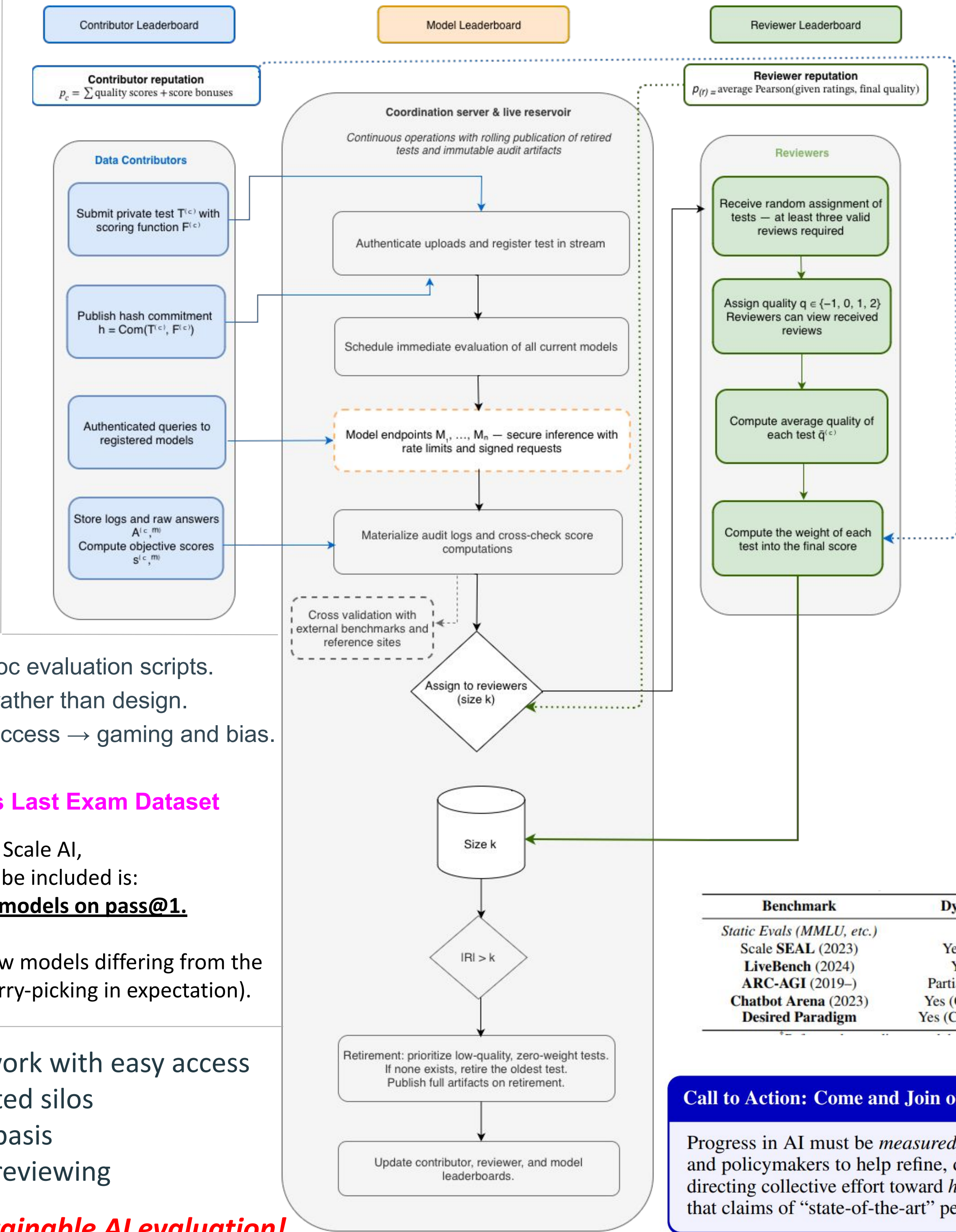
Example 2: Bias in Humanity’s Last Exam Dataset

In Humanity’s Last Exam [1] dataset by Scale AI, *a necessary condition* for a problem to be included is: **The problem is unsolved by 5 specific models on pass@1.**

This creates an inherent bias where new models differing from the 5 selected models will look better (cherry-picking in expectation).

End-to-End Workflow of PeerBench Prototype

Available at: www.peerbench.ai



Our Proposal - PeerBench: Live, Community-Governed Benchmarking Platform

Actors

- Data Contributors:** Author tests with executable scoring; Receive reputation from data quality determined by reviews
- Reviewers:** Provide ordinal ratings; accuracy vs. consensus determines weight.
- Model Creators:** Register models; expose inference endpoints;
- Coordination Server:** Orchestrates cross-validation and public leaderboards.
- End Users:** Researchers, regulators, practitioners; Consult live leaderboards with uncertainty thresholds.

Three Leaderboards

- Data Contributor Leaderboard:** Cumulative test quality + verification bonuses.
- Reviewer Leaderboard:** Alignment with consensus quality.
- Model Leaderboard:** Weighted by test quality for fair, robust scoring.

Temporal Fairness: Scheduling Trade-offs

- Immediate Scoring on Request** → responsiveness; risk: cross-period contamination / comparability.
- Synchronized Evaluation Windows** → strongest fairness; slower iteration.

Our Hybrid Approach: Data split

Part is used for immediate scoring for instant responsiveness; The rest is used for periodic windows for cross-cohort fairness and comparability.

Security and Audits

- Peer Review and Test Revelation Scheme for Data Quality Assurance:** A small random portion of live tests revealed privately to reviewers for peer review. After retirement, all tests are revealed for further check on quality and consistencies.
- Slashing & Incentives:** Collateral and rewards/punishments align behavior; platform-sustainable economics.

| Benchmark | Dynamic Update | Data Source Diversity | Transparency | Contamination Resistance | Data Quality Control |
|---------------------------|--------------------------|---------------------------|------------------------------|--------------------------|--|
| Static Evals (MMLU, etc.) | No | Single (Originating Team) | Yes (Public test sets) | No [‡] | Opaque; Community-Reliant [‡] |
| Scale SEAL (2023) | Yes (Continuous) | Single (Scale AI) | No (Private test sets) | Yes (Proprietary) | Opaque; Vendor-Internal [‡] |
| LiveBench (2024) | Yes (Monthly) | Single (Research Team) | Yes (Public post-evaluation) | Partial [‡] | Opaque; Team-Internal [‡] |
| ARC-AGI (2019–) | Partial (Episodic Sets) | Single (Organizers) | Yes (Public test sets) | Partial [‡] | Opaque; Expert-Driven [‡] |
| Chatbot Arena (2023) | Yes (Ongoing Prompts) | Yes (Crowdsourced) | Yes (Public prompts) | N/A [§] | Limited (Elo-Based) [‡] |
| Desired Paradigm | Yes (Continuous Rolling) | Yes (Validator Network) | Yes (Public post-evaluation) | Yes (By Design) | Transparent; Unified* |

References

- [1] Long Phan, Alice Gatti, Ziwen Han, Nathaniel Li, Josephina Hu, Hugh Zhang, Chen Bo Calvin Zhang et al. "Humanity's last exam." arXiv preprint arXiv:2501.14249 (2025).
[2] Zerui Cheng., Stella Wahnig, Ruchika Gupta, Samiul Alam, Tassallah Abdullahi, João Alves Ribeiro, Christian Nielsen-Garcia et al. "Benchmarking is Broken-Don't Let AI be its Own Judge." arXiv preprint arXiv:2510.07575 (2025).

Call to Action: Come and Join our Community at www.peerbench.ai!

Progress in AI must be *measured*, not merely marketed. We invite researchers, practitioners, and policymakers to help refine, deploy, and steward this emerging evaluation paradigm. By directing collective effort toward *how* we measure, we protect the integrity of *what* we build, so that claims of “state-of-the-art” performance once again carry demonstrable scientific weight.

TL;DR: We shouldn’t rely on people’s courtesy and goodwill for fair and sustainable AI evaluation!

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