



让多智能体协作的进展可积累：面向长程 机器学习的AI Agent

Toward Autonomous Long-Horizon
Engineering for ML Research

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➤ ML Research Engineering: 在固定时间/GPU预算内，把一篇论文或一个研究目标，变成可运行、可验证、可迭代改进的 ML 系统

Paper Bench

复现20篇ICML论文（包含环境安装，数据模型下载，以及baseline的复现）

MLE Bench Lite

进行Kaggle竞赛，并与人类榜单比较

21% vs 41%

PaperBench: best agent vs top ML PhDs

24h/task

realistic long-horizon budget

➤四大挑战:

Underspecification

论文不是完整 specification, 关键实现细节常常隐含或缺失

System setup

数据、模型、依赖、CUDA、评测脚本都会成为真正瓶颈

Delayed feedback

实验几小时后才返回, 失败原因还常常混杂

State continuity

后续决策必须正确继承早期假设、代码变更、实验结果

关键难点: 反馈延迟且混杂, 进展必须跨阶段、跨角色、跨多轮调用持续累积。

Core Insight: Long-running Agent needs continuity



- 智能体调用是transient，而长程问题必须cumulative
- 系统需要保存“未来会用到的证据”

Role continuity

同一智能体下次回来时，能恢复它之前试过什么、假设什么、失败在哪里

Project continuity

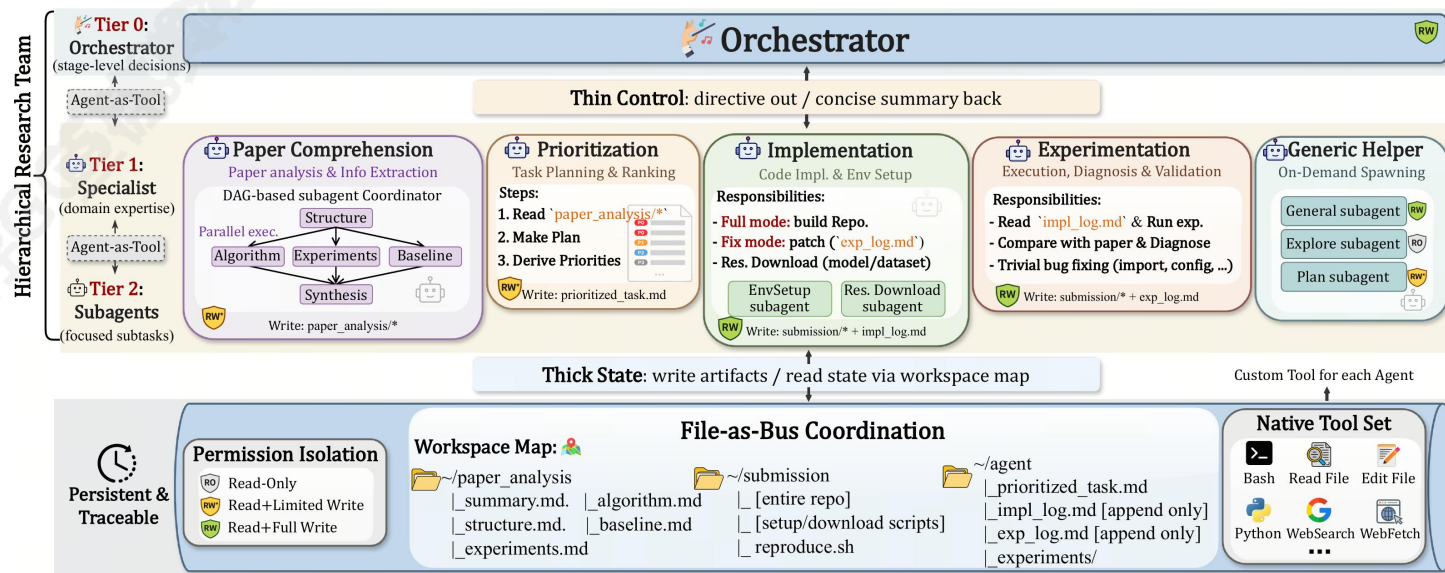
不同角色围绕同一套 evidence 协作，而不是依赖压缩过的 conversational handoff

transient activity → durable progress

AiScientist: thin control over thick state

➤ Orchestrator 只保留 stage-level control

➤ 详细证据沉淀在 File-as-Bus workspace 中，由智能体按需读取。



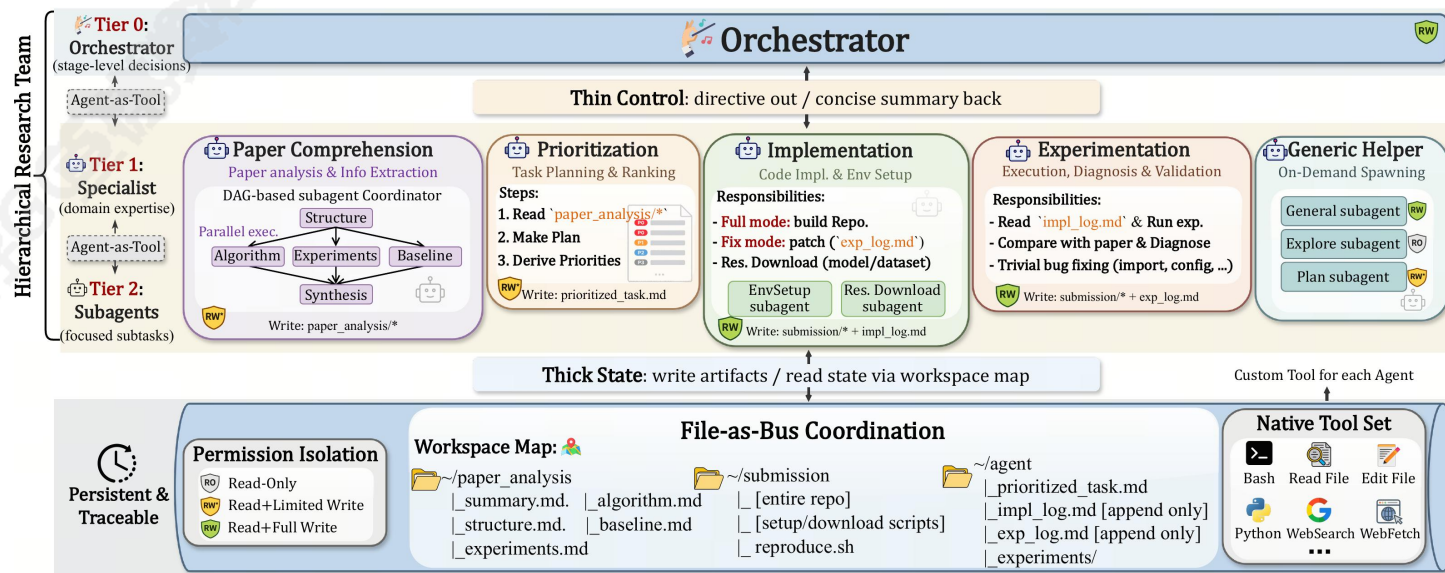
Thin control: concise directives + workspace map

Thick state: durable artifacts + role-readable evidence

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Thin control: concise directives + workspace map

Thick state: durable artifacts + role-readable evidence

File-as-Bus: 从共享文件夹到 protocol



➤每个 artifact 都有 purpose、update mode、writer 和 readers;
workspace 因此成为 collaboration contract

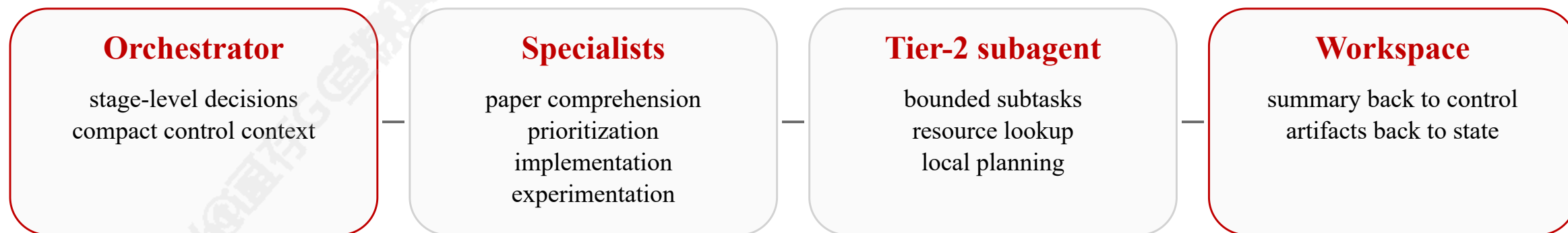
Update mode	What it preserves	Examples
Versioned artifact	当前 canonical state + 可追溯修订	paper_analysis/*.md, prioritized_task.md
Append-only log	按时间保留失败、诊断、决策证据	impl_log.md, exp_log.md
Mutable runnable artifact	真实可执行项目状态	submission/, setup/, reproduce.sh

关键点: 不是把所有东西塞进 context, 而是让 agent 能通过 workspace map 找到“该读什么证据”

Hierarchical team: delegation 是控制动作



➤ Orchestrator 把 specialist invocation 当作 tool action; 只有下一步需要局部长上下文或专业能力时才 delegation



关键点：不是把所有东西塞进 context，而是让 agent 能通过 **workspace map** 找到“**该读什么证据**”

Evidence loop: delayed feedback 变成证据

- 早期先形成 runnable scaffold
- 后续通过 implementation $\leftrightarrow$ experimentation $\leftrightarrow$ validation 的循环，把失败、metric gap 和修复记录下来



Loop invariant: 每轮输出都必须留下后续能 inspect 的 evidence: code-side decisions、failed runs、metrics、diagnoses、unresolved blockers

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Main Results

- AiScientist 在 paper replication 和 competition-style ML improvement 两类长链路 (24h) 任务上都有效

+9.92 / +11.15

PaperBench vs strongest matched baselines

81.82%

MLE-Bench Lite Any Medal under both
backbones

-31.82 pts

remove File-as-Bus on MLE Any Medal

**Long-horizon AI research is not merely a problem of stronger local reasoning;
it is a systems problem of maintaining cumulative, inspectable progress.**

PaperBench: 关键是复用 prior evidence

- IterativeAgent 已经增加交互，但 AiScientist 更高分且更低成本；说明 round count 不是充分解释

Backbone	Strongest baseline	AiScientist	Gain	Cost/task
Gemini-3-Flash	20.60	30.52	+9.92	\$15.67 vs \$27.44
GLM-5	22.58	33.73	+11.15	\$12.20 vs \$54.90
Frontier ref.	Codex/GPT-5.5: 29.45	Best: 33.73	+4.28	not matched baseline

Takeaway: extra interaction helps only when it is organized around cumulative research-engineering work.

MLE-Bench Lite: valid 只是起点, medal 才难

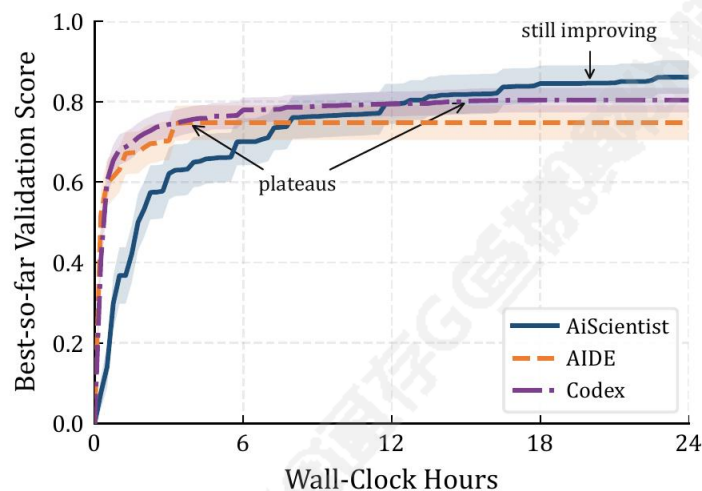
➤ 优势集中在 competitive outcomes, 而不是只生成 valid submission

System	Backbone	Valid	Above Median	Any Medal
AIDE	Gemini-3-Flash	87.88 ± 5.46	59.09 ± 2.62	45.45 ± 0.00
LoongFlow	Gemini-3-Flash	77.27 ± 0.00	77.27 ± 0.00	77.27 ± 0.00
AiScientist	Gemini-3-Flash	100.00 ± 0.00	86.36 ± 0.00	81.82 ± 0.00
ML-Master 2.0	GLM-5	100.00 ± 0.00	80.30 ± 1.52	65.15 ± 1.52
AiScientist	GLM-5	100.00 ± 0.00	89.39 ± 1.52	81.82 ± 0.00

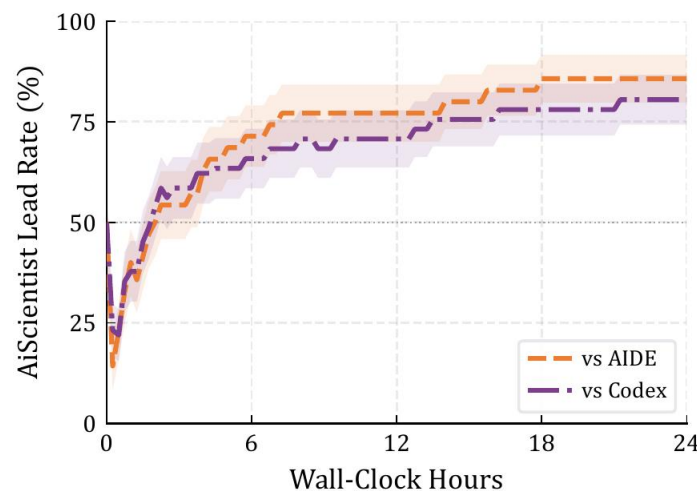
Codex/GPT-5.5 xhigh frontier harness: Any Medal 68.18 ± 2.62 ; AiScientist exceeds by 13.64 points.

Dynamics: 慢启动, 但后半程继续涨

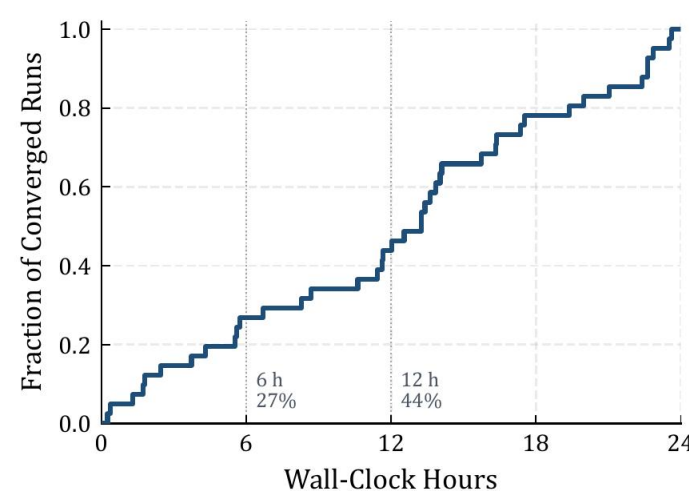
➤ 早期投入理解、规划和 scaffold; 优势在后半程逐步扩大



(a) magnitude



(b) breadth

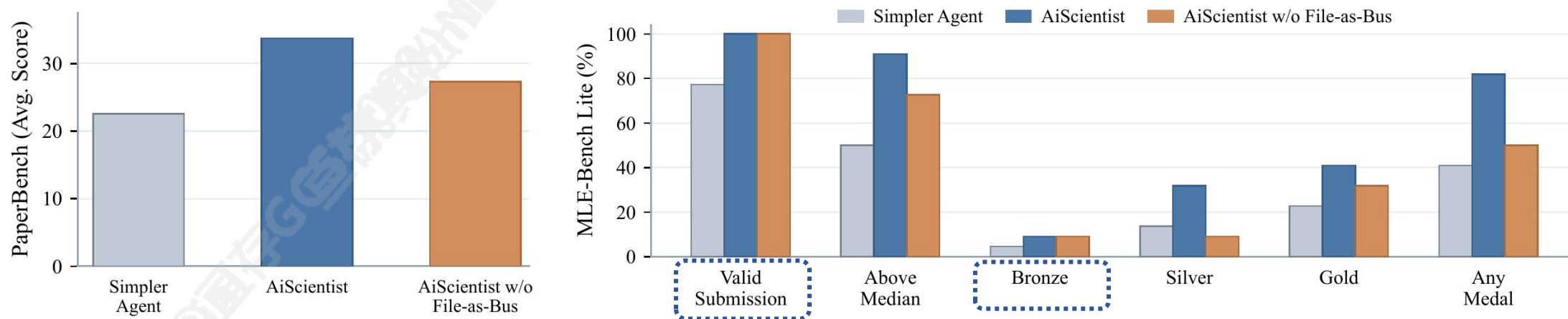


(c) when final best appears

Insight: long-horizon advantage is not one lucky late task; it broadens across paired runs and strengthens over the full 24h budget.

Ablation: File-as-Bus 支撑后期 refinement

➤ 去掉 File-as-Bus 后, validity 基本保留, 但 medal outcomes 大幅下降



-6.41 pts

PaperBench w/o File-as-Bus

100% valid

MLE validity preserved

-31.82 pts

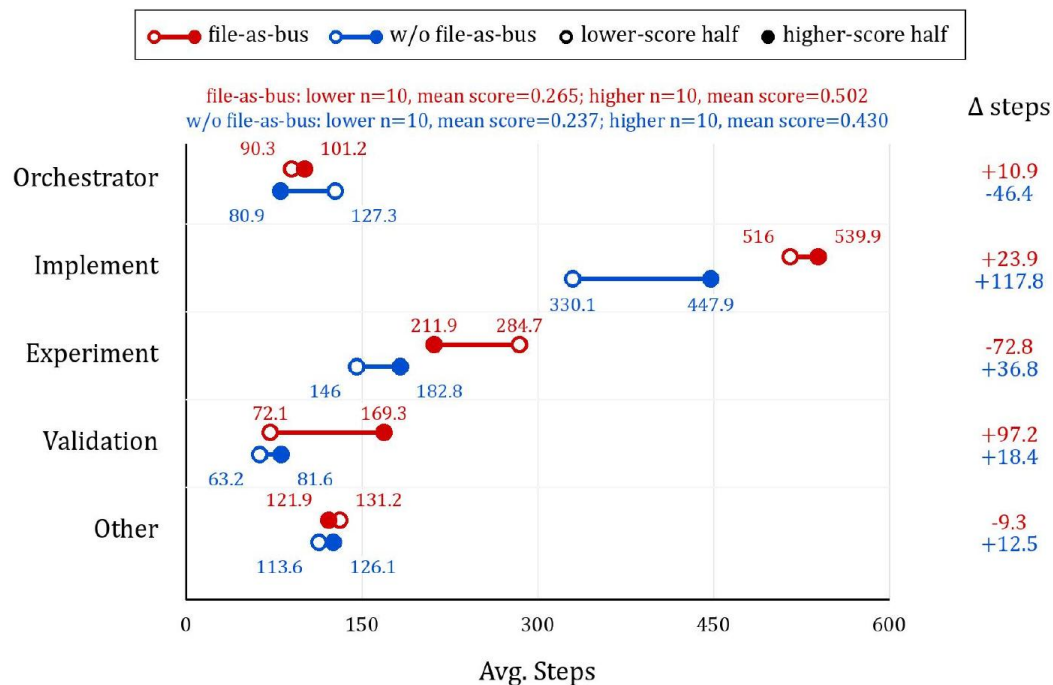
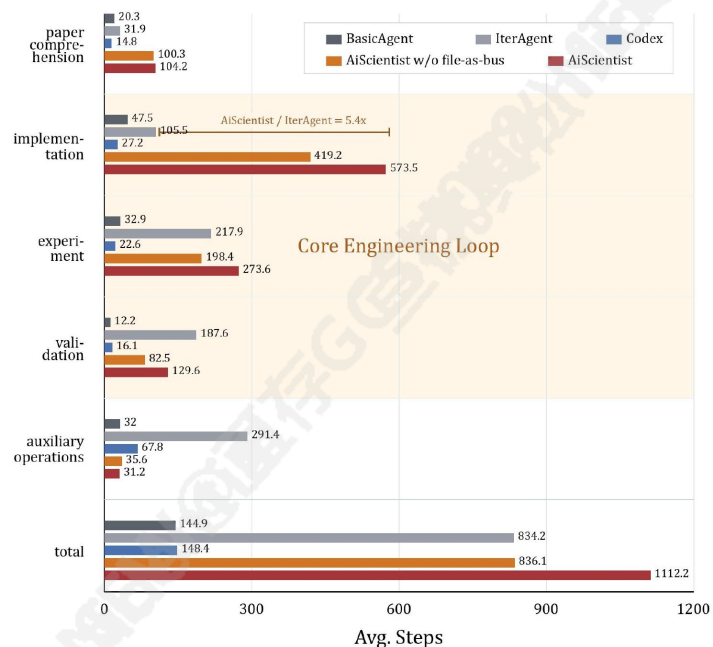
MLE Any Medal drop

+22.73 pts

hierarchy helps Above Median

Behavior: 成功不是多试，而是更早闭环

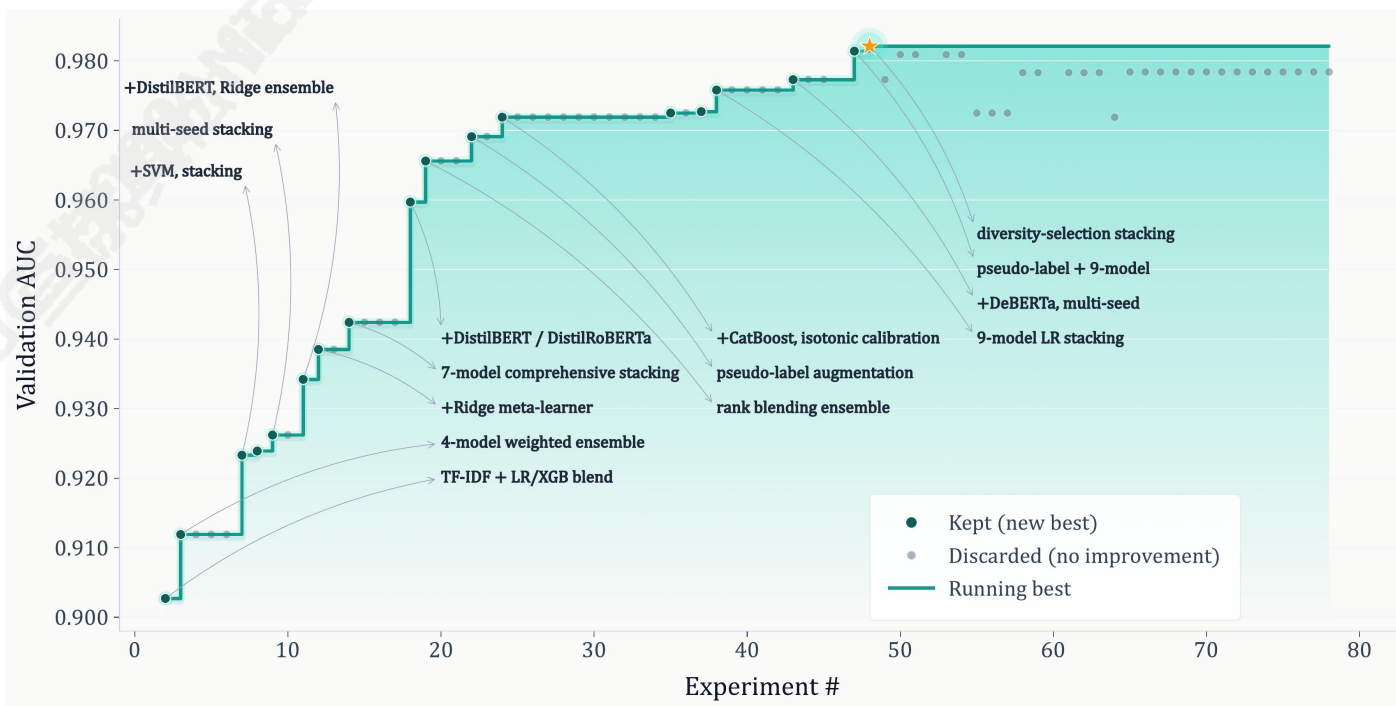
➤ 有 File-as-Bus 时，高分轨迹更早转向 validation/closure



**Do not read this as “more steps = better”: Codex is a strong low-step reference.
The key question is where effort is spent.**

Case: 23h 内 74 次实验循环

➤ Detecting Insults: AUC 0.903→0.982, 18 次 best-so-far 更新



Case-level lesson: experiment records are memory, not bookkeeping.



AiScientist

A File-as-Bus Research Lab

对 multi-agent 系统设计的启示

➤如果任务需要跨数小时/数天累积进展，agent framework 应该把 state design 当作 first-class design object

- 把 workspace 设计成 system of record，而不是 chat transcript 的附属品。
- 给 artifacts 明确 purpose、update mode、owner 和 consumer。
- 把 control summary 和 evidence substrate 分离：thin control, thick state。
- 评价 late-budget refinement：只看 first-pass success 会漏掉核心能力。



感谢聆听



Paper



Repo

Demo轻松上手
Paper/MLE bench打榜代码