Agentic Context Engineering: Evolving Contexts for Self-Improving Language Models

Agentic Context Engineering：為自我改進語言模型演化情境

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Abstract

摘要

Large language model (LLM) applications such as agents and domain-specific reasoning increasingly rely on context adaptation-modifying inputs with instructions, strategies, or evidence, rather than weight updates. Prior approaches improve usability but often suffer from brevity bias, which drops domain insights for concise summaries, and from context collapse, where iterative rewriting erodes details over time. Building on the adaptive memory introduced by Dynamic Cheatsheet, we introduce ACE (Agentic Context Engineering), a framework that treats contexts as evolving playbooks that accumulate, refine, and organize strategies through a modular process of generation, reflection, and curation. ACE prevents collapse with structured, incremental updates that preserve detailed knowledge and scale with long-context models. Across agent and domain-specific benchmarks, ACE optimizes contexts both offline (e.g., system prompts) and online (e.g., agent memory), consistently outperforming strong baselines: $+10.6\%$ on agents and $+8.6\%$ on finance, while significantly reducing adaptation latency and rollout cost. Notably, ACE could adapt effectively without labeled supervision and instead by leveraging natural execution feedback. On the AppWorld leaderboard, ACE matches the top-ranked production-level agent on the overall average and surpasses it on the harder test-challenge split, despite using a smaller open-source model. These results show that comprehensive, evolving contexts enable scalable, efficient, and self-improving LLM systems with low overhead.

大型語言模型 (LLM) 應用（例如 agents 與特定領域推理）越來越仰賴上下文調適——以指令、策略或證據來修改輸入，而非更新權重。先前的方法雖然提升了可用性，但常受到「簡潔偏誤」（brevity bias）的影響，會為了摘要的簡潔而丟失領域洞見；以及「上下文崩塌」（context collapse），在反覆改寫中隨時間侵蝕細節。建立在 Dynamic Cheatsheet 引入的自適應記憶之上，我們提出 ACE（Agentic Context Engineering），一個將上下文視為不斷演進的手冊的框架，透過模組化的生成、反思與策整（curation）流程來累積、精練和組織策略。ACE 以結構化、漸進式的更新防止崩塌，能保留詳細知識並能隨長上下文模型擴展。在跨代理與特定領域基準測試中，ACE 同時優化離線（例如 system prompts）與線上（例如 agent memory）上下文，持續優於強基線：agents 上為 $+10.6\%$ 、金融領域為 $+8.6\%$ ，同時顯著降低適配延遲與部署成本。 值得注意的是，ACE 能在沒有標記式監督的情況下透過利用自然執行回饋有效調整。在 AppWorld 排行榜上，ACE 在整體平均表現上與排名第一的生產級代理匹敵，並在較困難的 test-challenge 分組上超越該代理，儘管它使用的是較小的開源模型。這些結果顯示，全面且不斷演進的上下文使得 LLM 系統能以低資源開銷達成可擴展、高效率與自我改進的能力。

1 引言

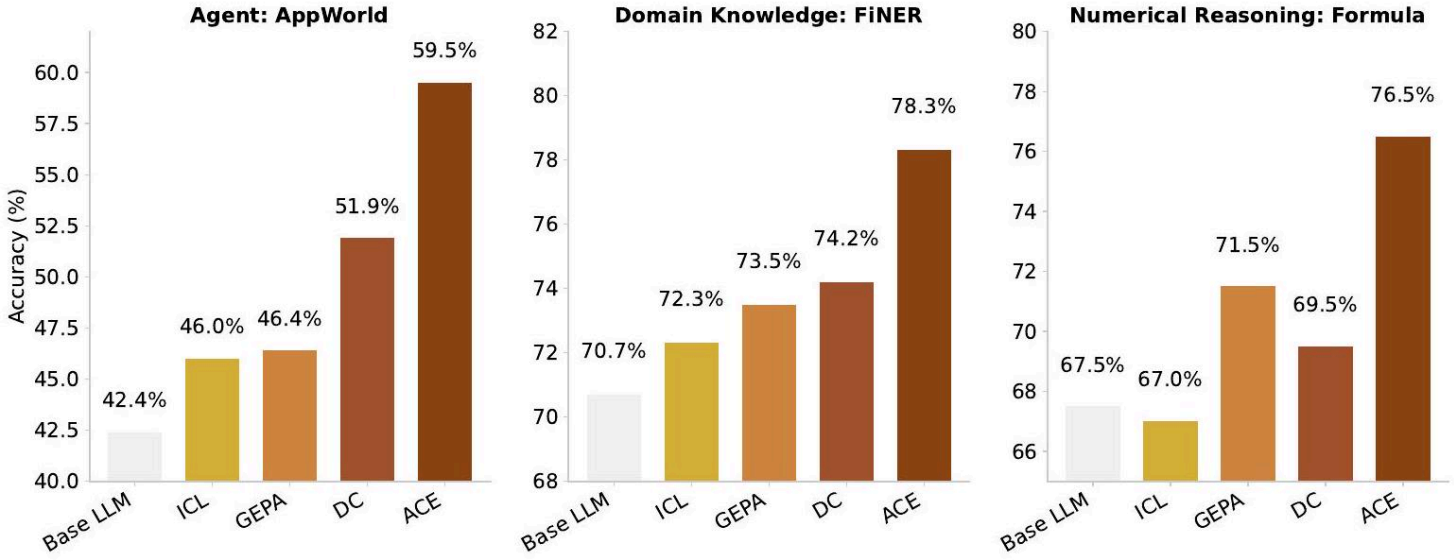

Figure 1: Figure 1: Overall Performance Results. Our proposed framework, ACE, consistently outperforms strong baselines across agent and domain-specific reasoning tasks.

圖 1：整體效能結果。我們提出的框架 ACE 在代理與領域特定推理任務上穩定地優於強力基準。

Modern AI applications based on large language models (LLMs), such as LLM agents [49,52] and compound AI systems [55], increasingly depend on context adaptation. Instead of modifying model weights, context

現代以大型語言模型（LLM）為基礎的 AI 應用，如 LLM agents [49,52] 與 compound AI systems [55]，日益仰賴上下文適應。與其修改模型權重，更多情況下是透過調整上下文來進行。

adaptation improves performance after model training by incorporating clarified instructions, structured reasoning steps, or domain-specific input formats directly into the model's inputs. Contexts underpin many AI system components, including system prompts that guide downstream tasks [4,36], memory that carries past facts and experiences [41,48], and factual evidence that reduces hallucination and supplements knowledge [6].

在模型訓練後，透過在模型輸入中直接加入明確化的指令、結構化的推理步驟或領域特定的輸入格式，可以改善效能。上下文支撐了許多 AI 系統元件，包括用以引導下游任務的 system prompts [4,36]、承載過去事實與經驗的記憶 [41,48]，以及可減少幻覺並補充知識的事實性證據 [6]。

Adapting through contexts rather than weights offers several key advantages. Contexts are interpretable and explainable for users and developers [45, 47], allow rapid integration of new knowledge at runtime [7, 27], and can be shared across models or modules in a compound system [23]. Meanwhile, advances in longcontext LLMs [39] and context-efficient inference such as KV cache reuse [17,51] are making context-based approaches increasingly practical for deployment. As a result, context adaptation is emerging as a central paradigm for building capable, scalable, and self-improving AI systems.

透過上下文而非權重進行調適具有幾項重要優勢。上下文對使用者與開發者來說可解釋且具可說明性 [45, 47]，允許在執行時快速整合新知識 [7, 27]，並能在複合系統中的不同模型或模組之間共享 [23]。同時，長上下文 LLMs 的進展 [39] 以及如 KV cache reuse [17,51] 等上下文效率化推理技術，正使基於上下文的方法在部署上越來越實用。因此，上下文調適正逐漸成為建構具能力、可擴展且能自我改進的 AI 系統的核心範式。

Despite this progress, existing approaches to context adaptation face two key limitations. First, a brevity bias: many prompt optimizers prioritize concise, broadly applicable instructions over comprehensive accumulation. For example, GEPA [4] highlights brevity as a strength, but such abstraction can omit domain-specific heuristics, tool-use

guidelines, or common failure modes that matter in practice [16]. This objective aligns with validation metrics in some settings, but often fails to capture the detailed strategies required by agents and knowledge-intensive applications. Second, context collapse: methods that rely on monolithic rewriting by an LLM often degrade into shorter, less informative summaries over time, causing sharp performance declines (Figure 2). In domains such as interactive agents [38, 43,57], domain-specific programming [53,56], and financial or legal analysis [18,33,44], strong performance depends on retaining detailed, task-specific knowledge rather than compressing it away.

儘管已有進展，現有的情境調適方法仍面臨兩項主要限制。首先是簡短偏好：許多提示優化器偏好簡潔、廣泛適用的指示，而非全面累積。例如，GEPA [4] 將簡潔視為優勢，但此類抽象化可能遺漏實務上重要的領域特定啟發式、工具使用指南或常見失敗模式 [16]。在某些情境下，這一目標與驗證指標相符，但常常無法捕捉代理與知識密集型應用所需的詳細策略。其次是情境坍縮：倚賴 LLM 進行整體改寫的方法經常會隨時間退化成較短且資訊量較低的摘要，導致性能急劇下降（圖 2）。在互動型代理 [38, 43,57]、領域特定程式設計 [53,56] 以及金融或法律分析 [18,33,44] 等領域，強健的表現依賴於保留詳細的任務特定知識，而非將其壓縮消失。

As applications such as agents and knowledge-intensive reasoning demand greater reliability, recent work has shifted toward saturating contexts with abundant, potentially useful information [11,12,22], enabled by advances in long-context LLMs [34, 39]. We argue that contexts should function not as concise summaries, but as comprehensive, evolving playbooks-detailed, inclusive, and rich with domain insights. Unlike humans, who often benefit from concise generalization, LLMs are more effective when provided with long, detailed contexts and can distill relevance autonomously [22,31,41]. Thus, instead of compressing away domain-specific heuristics and tactics, contexts should preserve them, allowing the model to decide what matters at inference time.

隨著像 agents 和需要大量知識推理的應用要求更高的可靠性，近期研究已轉向以充斥豐富且可能有用資訊的上下文為主 [11,12,22]，這得以透過長上下文 LLMs 的進展實現 [34, 39]。我們主張上下文不應只當作簡潔的摘要，而應成為全面且不斷演化的操作手冊——詳盡、包羅萬象且充滿領域洞見。與通常從簡明概括中獲益的人類不同，LLMs 在提供長而詳細的上下文時表現更佳，且能自主萃取相關性 [22,31,41]。因此，上下文不應壓縮或刪去領域特定的啟發式與策略，而應保留它們，讓模型在推論時自行決定何者重要。

To address these limitations, we introduce ACE (Agentic Context Engineering), a framework for comprehensive context adaptation in both offline settings (e.g., system prompt optimization) and online settings (e.g., test-time memory adaptation). Rather than compressing contexts into distilled summaries, ACE treats them as evolving playbooks that accumulate and organize strategies over time. Building on the agentic architecture of Dynamic Cheatsheet [41], ACE incorporates a modular workflow of generation, reflection, and curation, while adding structured, incremental updates guided by a grow-and-refine principle. This design preserves detailed, domain-specific knowledge, prevents context collapse, and yields contexts that remain comprehensive and scalable throughout adaptation.

為了解決這些限制，我們提出 ACE（Agentic Context Engineering），一個用於在離線情境（例如系統提示優化）與線上情境（例如測試時記憶適應）中進行全面性情境調適的框架。ACE 並非將情境壓縮為精簡的摘要，而是將其視為隨時間累積與組織策略的演進劇本。基於 Dynamic Cheatsheet [41] 的 agentic 架構，ACE 採用生成、反思與策展的模組化工作流程，並加入由成長與精練原則指引的結構化漸進更新。此設計保留了詳細且特定領域的知識，防止情境崩潰，並產生在整個適應過程中仍保持全面性與可擴展性的情境。

We evaluate ACE on two categories of LLM applications that most benefit from comprehensive, evolving contexts: (1) agents [43], which require multi-turn reasoning, tool use, and environment interaction, where accumulated strategies can be reused across episodes; and (2) domain-specific benchmarks, which demand specialized tactics and knowledge, where we focus on financial analysis [33,44]. Our key findings are:

我們在兩類最受益於完整且不斷演進的上下文的 LLM 應用上評估 ACE：(1) 代理（agents）[43]，這類應用需要多回合推理、工具使用與環境互動，累積的策略可跨多個情節重複使用；以及 (2) 領域特定基準測試（domain-specific benchmarks），這類測試要求專門的戰術與知識，我們聚焦於財務分析 [33,44]。我們的主要發現是：

ACE consistently outperforms strong baselines, yielding average gains of 10.6% on agents and 8.6% on domain-specific benchmarks, across both offline and online adaptation settings.

ACE 持續優於強力基線，在離線與線上自適應設定下，於代理上平均帶來 10.6% 的增益、於領域特定基準上帶來 8.6% 的增益。

ACE is able to construct effective contexts without labeled supervision, instead leveraging execution feedback and environment signals-key ingredients for self-improving LLMs and agents.

ACE 能在沒有標註監督的情況下建構有效的上下文，而是利用執行回饋與環境訊號——這些是自我改進 LLM 與代理的關鍵要素。

On the AppWorld benchmark leaderboard [5], ACE matches the top-ranked production-level agent IBMCUGA [35] (powered by GPT-4.1) on average and surpasses it on the harder test-challenge split, while using a smaller open-source model (DeepSeek-V3.1).

在 AppWorld 基準排行榜 [5] 上，ACE 平均上可與排名第一的量產級代理 IBMCUGA [35]（由 GPT-4.1 提供動力）相匹敵，並在較難的 test-challenge 切分上超越它，同時使用較小的開源模型 DeepSeek-V3.1。

ACE requires significantly fewer rollouts and lower dollar costs, and achieves 86.9% lower adaptation latency (on average) than existing adaptive methods, demonstrating that scalable self-improvement can be achieved with both higher accuracy and lower overhead.

ACE 需要顯著更少的嘗試次數和較低的金額成本，並且在適應延遲方面（平均）比現有自適應方法低 86.9% ，顯示可擴展的自我改進可以在更高準確度與更低開銷下達成。

2 Background and Motivation

2 背景與動機

2.1 Context Adaptation

2.1 上下文調適

Context adaptation (or context engineering) refers to methods that improve model behavior by constructing or modifying inputs to an LLM, rather than altering its weights. The current state of the art leverages natural language feedback [4, 40, 54]. In this paradigm, a language model inspects the current context along with signals such as execution traces, reasoning steps, or validation results, and generates natural language feedback on how the context should be revised. This feedback is then incorporated into the context, enabling iterative adaptation. Representative methods include Reflexion [40], which reflects on failures to improve agent planning; TextGrad [54], which optimizes prompts via gradient-like textual feedback; GEPA [4], which refines prompts iteratively based on execution traces and achieves strong performance, even surpassing reinforcement learning approaches in some settings; and Dynamic Cheatsheet [41], which constructs an external memory that accumulates strategies and lessons from past successes and failures during inference. These natural language feedback methods represent a major advance, offering flexible and interpretable signals for improving LLM systems beyond weight updates.

情境調適（或稱情境工程）是指透過建構或修改輸入到 LLM 的內容來改善模型行為的方法，而非變更其權重。現今的最先進方法利用自然語言回饋 [4, 40, 54] 。在此範式中，語言模型會檢視當前情境以及執行記錄、推理步驟或驗證結果等訊號，並產生關於應如何修改情境的自然語言回饋。這些回饋隨後被納入情境中，從而實現迭代式的調適。具代表性的方法包括 Reflexion [40]，透過反思失敗來改善代理人的規劃；TextGrad [54]，透過類似梯度的文字回饋來優化提示；GEPA [4]，根據執行記錄迭代精煉提示並達到強勁的表現，甚至在某些情境超越強化學習方法；以及 Dynamic Cheatsheet [41]，在推理過程中構建一個累積過去成功與失敗策略與經驗的外部記憶。 這些以自然語言為基礎的回饋方法代表了一項重大進展，提供了靈活且具可解釋性的信號，用以在不僅限於權重更新的情況下改善 LLM 系統。

2.2 Limitations of Existing Context Adaptation Methods

2.2 現有情境調適方法的限制

The Brevity Bias. A recurring limitation of context adaptation methods is brevity bias: the tendency of optimization to collapse toward short, generic prompts. Gao et al. [16] document this effect in prompt optimization for test generation, where iterative methods repeatedly produced near-identical instructions (e.g., “Create unit tests to ensure methods behave as expected”), sacrificing diversity and omitting domainspecific detail. This convergence not only narrows the search space but also propagates recurring errors across iterations, since optimized prompts often inherit the same faults as their seeds. More broadly, such bias undermines performance in domains that demand detailed, context-rich guidance-such as multi-step agents, program synthesis, or knowledge-intensive reasoning-where success hinges on accumulating rather than compressing task-specific insights.

簡短偏向（Brevity Bias）。情境調適方法一再出現的限制是簡短偏向：優化傾向收斂到簡短且通用的提示。Gao 等人 [16] 在測試生成的提示優化中記錄了此效應，迭代方法反覆產生出近乎相同的指示（例如：「建立單元測試以確保方法如預期運作」），以致犧牲了多樣性並省略了領域特定的細節。這種收斂不僅縮小了搜尋空間，還會在多次迭代中傳播反覆出現的錯誤，因為被優化的提示常常繼承自原始提示的相同缺陷。更廣泛地說，這種偏向削弱了在需要詳細、情境豐富指導的領域中的效能——例如多步驟代理、程式合成或知識密集型推理——在這些領域中，成功依賴的是累積而非壓縮任務特定的見解。

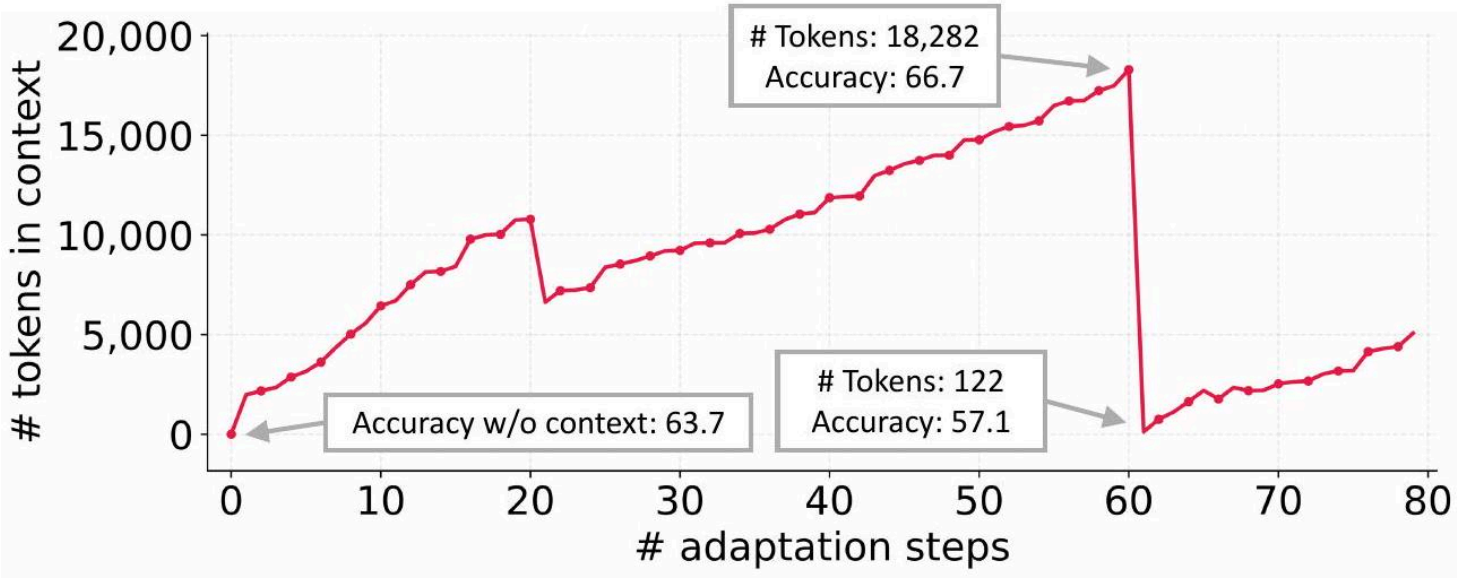

Figure 2: Figure 2: Context Collapse. Monolithic rewriting of context by an LLM can collapse it into shorter, less informative summaries, leading to sharp performance drops.

圖 2：圖 2：上下文崩潰。LLM 對上下文進行整體改寫時，可能會將其壓縮為更短且資訊量較少的摘要，導致性能急劇下降。

Context Collapse. In a case study on the AppWorld benchmark [43], we observe a phenomenon we call context collapse, which arises when an LLM is tasked with fully rewriting the accumulated context at each adaptation step. As the context grows large, the model tends to compress it into much shorter, less informative summaries, causing a dramatic loss of information. For instance, at step 60 the context contained

上下文崩潰。在 AppWorld 基準測試 [43] 的案例研究中，我們觀察到一種我們稱為「上下文崩潰」的現象，當 LLM 被指派在每個自我調整步驟中完全重寫累積的上下文時會出現此情況。隨著上下文變得龐大，模型傾向於將其壓縮為更短且資訊量較少的摘要，導致資訊大幅流失。例如，在第 60 步時上下文包含

18,282 tokens and achieved an accuracy of 66.7, but at the very next step it collapsed to just 122 tokens, with accuracy dropping to 57.1 -worse than the baseline accuracy of 63.7 without adaptation. While we highlight this through Dynamic Cheatsheet [41], the issue is not specific to that method; rather, it reflects a fundamental risk of end-to-end

context rewriting with LLMs, where accumulated knowledge can be abruptly erased instead of preserved.

18,282 個 token，並達到 66.7 的準確率，但在下一個步驟它崩潰到僅剩 122 個 token，準確率降到 57.1——甚至比未進行調整的基線準確率 63.7 還差。我們透過 Dynamic Cheatsheet [41] 強調此現象，但此問題並非該方法所專屬；相反地，它反映了使用 LLM 進行端到端上下文重寫的根本風險，累積的知識可能被突然抹去而非保留。

The Generated ACE Playbook on AppWorld

在 AppWorld 上生成的 ACE Playbook

STRATEGIES AND HARD RULES

策略與嚴格規則

[shr-00009]
When processing time-sensitive transactions involving specific relationships: always resolve identities from the correct source app (phone contacts), use proper datetime range comparisons instead of string matching, and verify all filtering criteria (relationship + time) are met before processing items. This ensures accurate identification and processing of the right transactions.

在處理涉及特定關係的即時交易時：務必從正確的來源應用程式（電話聯絡人）解析身份，使用適當的日期時間範圍比較而非字串比對，並在處理項目前驗證所有篩選條件（關係 + 時間）是否符合。這可確保準確識別並處理正確的交易。

USEFUL CODE SNIPPETS AND TEMPLATES

有用的程式碼片段與範本

[code-00013]
For efficient artist aggregation when processing songs, use defaultdict(list) to map song titles to artist names:

若要在處理歌曲時有效聚合藝術家，請使用 defaultdict(list) 將歌曲標題對應到藝術家名稱：

from collections import defaultdict artist_map = defaultdict(list) for song in songs:
artist_map[song[‘title’]].extend([artist[‘name’] for artist in song[‘artists’]])

TROUBLESHOOTING AND PITFALLS

疑難排解與陷阱

[ts-00003]
If authentication fails, troubleshoot systematically: try phone number instead of email as username, clean credentials from supervisor, check API documentation for correct parameters etc. Do not proceed with workarounds.

如果認證失敗，請系統性地進行故障排除：嘗試使用電話號碼取代電子郵件作為使用者名稱、從主管那裡清除憑證、檢查 API 文件以確認正確的參數等。不要以替代方法繼續作業。

Figure 3: Example ACE-Generated Context on the AppWorld Benchmark (partially shown). ACE-generated contexts contain detailed, domain-specific insights along with tools and code that are readily usable, serving as a

comprehensive playbook for LLM applications.

圖 3：AppWorld 基準的 ACE 生成情境範例（部分顯示）。ACE 生成的情境包含詳細的領域特定見解，以及可立即使用的工具和程式碼，作為 LLM 應用的完整操作手冊。

3 Agentic Context Engineering (ACE)

We present ACE (Agentic Context Engineering), a framework for scalable and efficient context adaptation in both offline (e.g., system prompt optimization) and online (e.g., test-time memory adaptation) scenarios. Instead of condensing knowledge into terse summaries or static instructions, ACE treats contexts as evolving playbooks that continuously accumulate, refine, and organize strategies over time. Building on the agentic design of Dynamic Cheatsheet [41], ACE introduces a structured division of labor across three roles (Figure 4): the Generator, which produces reasoning trajectories; the Reflector, which distills concrete insights from successes and errors; and the Curator, which integrates these insights into structured context updates. This mirrors how humans learn-experimenting, reflecting, and consolidating-while avoiding the bottleneck of overloading a single model with all responsibilities.

我們提出 ACE（Agentic Context Engineering），一個在離線（例如系統提示優化）與線上（例如測試時記憶調適）情境中皆可擴展且高效的情境調適框架。ACE 並非將知識濃縮為簡短摘要或靜態指令，而是將情境視為不斷演進的策略手冊，隨時間持續累積、精煉與組織策略。基於 Dynamic Cheatsheet [41] 的自主代理設計，ACE 在三個角色之間引入結構化的分工（圖 4）：Generator（生成器），負責產出推理軌跡；Reflector（反思者），從成功與錯誤中提煉具體見解；以及 Curator（策展者），將這些見解整合為結構化的情境更新。這類似人類的學習方式——實驗、反思與鞏固——同時避免將所有職責壓在單一模型上的瓶頸。

To address the limitations of prior methods discussed in §2.2-notably brevity bias and context collapse-ACE introduces three key innovations: (1) a dedicated Reflector that separates evaluation and insight extraction from curation, improving context quality and downstream performance (§4.5); (2) incremental delta updates (§3.1) that replace costly monolithic rewrites with localized edits, reducing both latency and compute cost (§4.6); and (3) a grow-and-refine mechanism (§3.2) that balances steady context expansion with redundancy control.

為了解決第 2.2 節所討論的既有方法限制——特別是偏好簡短回應與上下文崩潰問題——ACE 引入三項關鍵創新：(1) 一個專門的 Reflector，將評估與洞見擷取從策展工作中分離，提升上下文品質與下游表現（§4.5）；(2) 增量的差分更新（§3.1），以局部編輯取代高成本的整體重寫，降低延遲與計算成本（§4.6）；以及 (3) 一個擴展與精煉機制（§3.2），在穩健擴充上下文與冗餘控制之間取得平衡。

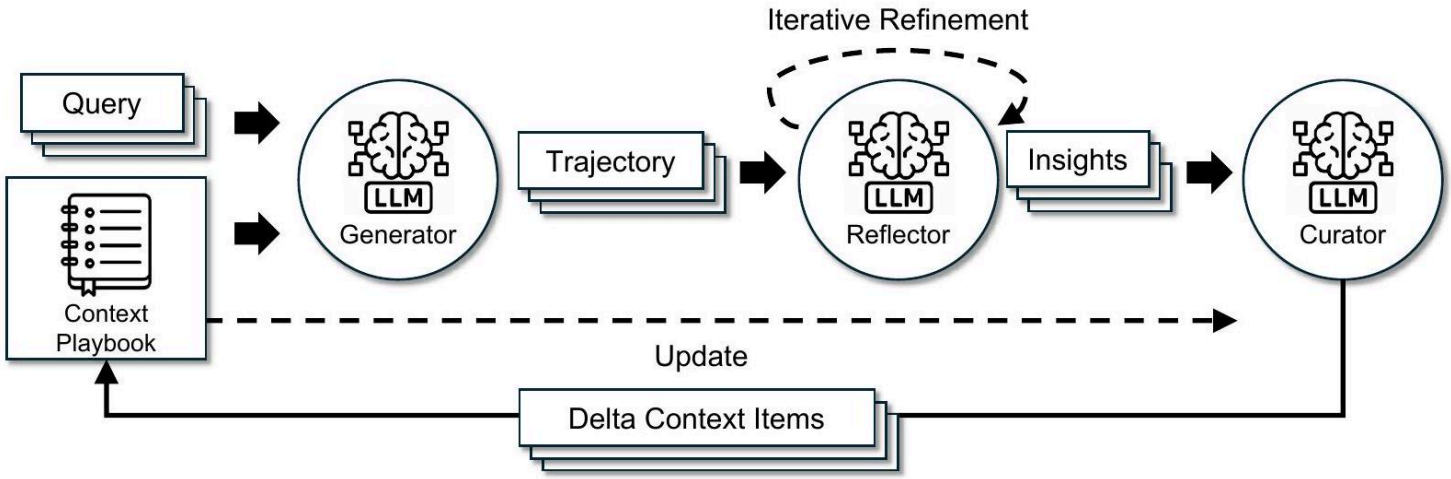

Figure 3: Figure 4: The ACE Framework. Inspired by Dynamic Cheatsheet, ACE adopts an agentic architecture with three specialized components: a Generator, a Reflector, and a Curator.

圖 3：圖 4：ACE 框架。受 Dynamic Cheatsheet 啟發，ACE 採用具行動能力的架構，包含三個專門化元件：Generator、Reflector 與 Curator。

As shown in Figure 4, the workflow begins with the Generator producing reasoning trajectories for new queries, which surface both effective strategies and recurring pitfalls. The Reflector critiques these traces to extract lessons, optionally refining them across multiple iterations. The Curator then synthesizes these lessons into compact delta entries, which are merged deterministically into the existing context by lightweight, non-LLM logic. Because updates are itemized and localized, multiple deltas can be merged in parallel, enabling batched adaptation at scale. ACE further supports multi-epoch adaptation, where the same queries are revisited to progressively strengthen the context.

如圖 4 所示，工作流程從 Generator 為新查詢產生推理軌跡開始，這些軌跡揭示了有效策略與反覆出現的陷阱。Reflector 對這些軌跡進行批判性檢視以萃取教訓，並可在多次迭代中選擇性地精煉它們。接著 Curator 將這些教訓綜合成精簡的 delta 條目，透過輕量的非-LLM 邏輯確定性地合併到現有上下文中。由於更新被條目化且區域化，數個 delta 可以並行合併，從而實現大規模的批次適應。ACE 更支援多輪(epoch)適應，在該流程中會重訪相同查詢以逐步強化上下文。

3.1 Incremental Delta Updates

3.1 漸進式 Delta 更新

A core design principle of ACE is to represent context as a collection of structured, itemized bullets, rather than a single monolithic prompt. The concept of a bullet is similar to the concept of a memory entry in LLM memory frameworks like Dynamic Cheatsheet [41] and A-MEM [48], but builds on top of that and consists of (1) metadata, including a unique identifier and counters tracking how often it was marked helpful or harmful; and (2) content, capturing a small unit such as a reusable strategy, domain concept, or common failure mode. When solving new problems, the Generator highlights which bullets were useful or misleading, providing feedback that guides the Reflector in proposing corrective updates.

ACE 的核心設計原則是將上下文表現為一組結構化、逐項列出的要點，而非單一的整體提示。要點（bullet）的概念類似于像 Dynamic Cheatsheet [41] 和 A-MEM [48] 這類 LLM 記憶框架中的記憶條目，但在此基礎上擴充，包含 (1) 元資料，包括唯一識別碼和追蹤被標記為有用或有害次數的計數器；以及 (2) 內容，捕捉一個小單位，例如可重用的策略、領域概念或常見失敗模式。在解決新問題時，Generator 會標記哪些要點是有幫助或具誤導性的，提供反饋以引導 Reflector 提出修正性更新。

This itemized design enables three key properties: (1) localization, so only the relevant bullets are updated; (2) fine-grained retrieval, so the Generator can focus on the most pertinent knowledge; and (3) incremental adaptation, allowing efficient merging, pruning, and de-duplication during inference.

這種逐項設計帶來三個關鍵特性：(1) 區域化，只更新相關的要點；(2) 細粒度檢索，使 Generator 能專注於最相關的知識；以及 (3) 逐步適應，允許在推理期間高效地合併、修剪和去重。

Rather than regenerating contexts in full, ACE incrementally produces compact delta contexts: small sets of candidate bullets distilled by the Reflector and integrated by the Curator. This avoids the computational cost and latency of full rewrites, while ensuring that past knowledge is preserved and new insights are steadily appended. As contexts grow, this approach provides the scalability needed for long-horizon or domain-intensive applications.

與其完全重生上下文，ACE 逐步產生緊湊的增量上下文（delta contexts）：由 Reflector 提煉並由 Curator 整合的小型候選子彈點集合。這避免了全面重寫的計算成本與延遲，同時確保過往知識被保留並穩定地附加新見解。隨著上下文擴展，這種做法為長期或領域密集型應用提供所需的可擴展性。

3.2 Grow-and-Refine

Beyond incremental growth, ACE ensures that contexts remain compact and relevant through periodic or lazy refinement. In grow-and-refine, bullets with new identifiers are appended, while existing bullets are updated in place (e.g., incrementing counters). A de-duplication step then prunes redundancy by comparing bullets via semantic embeddings. This refinement can be performed proactively (after each delta) or lazily (only when the context window

is exceeded), depending on application requirements for latency and accuracy.

除了漸進增長外，ACE 透過週期性或延遲的精煉確保上下文保持緊湊且相關。在 grow-and-refine 中，帶有新識別碼的子彈點會被附加，而現有子彈點則就地更新（例如，計數器遞增）。接著透過語意嵌入比較子彈點來執行去重步驟以修剪冗餘。根據應用對延遲和準確度的需求，這種精煉可以主動執行（每次增量後）或延遲執行（僅在超出上下文視窗時）。

Together, incremental updates and grow-and-refine maintain contexts that expand adaptively, remain interpretable, and avoid the potential variance introduced by monolithic context rewriting.

增量更新與 grow-and-refine 共同維持能自適應擴展、可解讀且能避免單體式上下文重寫所引入潛在變異的上下文。

4 Results

4 結果

Our evaluation of ACE shows that:

我們對 ACE 的評估顯示：

Enabling High-Performance, Self-Improving Agents. ACE enables agents to self-improve by dynamically refining their input context. It boosts accuracy on the AppWorld benchmark by up to 17.1% by learning to engineer better contexts from execution feedback alone, without needing ground-truth labels. This contextdriven improvement allows a smaller, open-source model to match the performance of the top-ranked proprietary agent on the leaderboard. (§4.3)

啟用高效能、自我改進的代理。ACE 使代理能透過動態精煉其輸入上下文來自我改進。它能在不需要真實標籤的情況下，僅從執行反饋學習構建更好的上下文，將 AppWorld 基準的準確率提升最多 17.1% 。這種以上下文為驅動的改進，使得一個較小的開源模型能匹配排行榜上排名第一的專有代理的表現。(§4.3)

Large Gains on Domain-Specific Benchmarks. On complex financial reasoning benchmarks, ACE delivers an average performance gain of 8.6% over strong baselines by constructing comprehensive playbooks with domain-specific concepts and insights. (§4.4)

在領域特定基準上大幅提升。在複雜的財務推理基準上，ACE 透過建構包含領域專屬概念與見解的完整操作手冊，相較於強力基線平均帶來 8.6% 的效能提升。(§4.4)

Effective by Design. Ablation studies confirm our design choices are key to success, with components like the Reflector and multi-epoch refinement each contributing substantial performance gains. (§4.5)

以設計為本的有效性。消融研究確認我們的設計選擇是成功的關鍵，像 Reflector 與多輪(epoch)精煉等元件各自帶來顯著的性能提升。(§4.5)

Lower Cost and Adaptation Latency. ACE achieves these gains efficiently, reducing adaptation latency by 86.9% on average, while requiring fewer rollouts and lower token dollar costs. (§4.6)

更低的成本與適應延遲。ACE 有效率地達成這些提升，平均將適應延遲降低 86.9% ，同時需要較少的 rollout 並降低每 token 的金錢成本。(§4.6)

4.1 Tasks and Datasets

4.1 任務與資料集

We evaluate ACE on two categories of LLM applications that benefit most from a comprehensive and evolving context: (1) agent benchmarks, which require multi-turn reasoning, tool use, and environment interaction, where agents can accumulate and reuse strategies across episodes and environments; and (2) domain-specific benchmarks, which demand mastery of specialized concepts and tactics, where we focus on financial analysis as a case study.

我們在兩類最能從全面且不斷演進的上下文受益的 LLM 應用上評估 ACE：(1) 代理基準，這類需要多輪推理、工具使用與環境互動，代理可在不同 episode 與環境間累積並重用策略；以及 (2) 領域專用基準，需精通專門概念與策略，我們以金融分析作為個案研究。

LLM Agent: AppWorld [43] is a suite of autonomous agent tasks involving API understanding, code generation, and environment interaction. It provides a realistic execution environment with common applications and APIs (e.g., email, file system) and tasks of two difficulty levels (normal and challenge). A public leaderboard [5] tracks performance, where, at the time of submission, the best system achieved only 60.3% average accuracy, highlighting the benchmark's difficulty and realism.

LLM 代理：AppWorld [43] 是一套自主代理任務，涵蓋 API 理解、程式碼生成與環境互動。它提供一個具現實性的執行環境，包含常見應用程式與 API（例如電子郵件、檔案系統），並提供兩種難度等級的任務（普通與挑戰）。一個公開排行榜 [5] 追蹤表現，提交時最佳系統的平均準確率僅為 60.3% ，凸顯該基準的困難度與真實性。

Financial Analysis: FiNER [33] and Formula [44] test LLMs on financial reasoning tasks that rely on the eXtensible Business Reporting Language (XBRL). FiNER requires labeling tokens in XBRL financial documents with one of 139 fine-grained entity types, a key step for financial information extraction in regulated domains. Formula focuses on extracting values from structured XBRL filings and performing computations to answer financial queries, i.e., numerical reasoning.

財務分析：FiNER [33] 與 Formula [44] 測試 LLMs 在依賴可擴充商業報告語言（XBRL）的財務推理任務上的表現。FiNER 要求在 XBRL 財務文件中為標記的詞元標註 139 種細緻的實體類型之一，這是受監管領域中財務資訊擷取的一項關鍵步驟。Formula 則專注於從結構化的 XBRL 報表中擷取數值並執行計算以回答財務查詢，即數值推理。

Evaluation Metrics. For AppWorld, we follow the official benchmark protocol and report Task Goal Completion (TGC) and Scenario Goal Completion (SGC) on both the test-normal and test-challenge splits. For FiNER and Formula, we follow the original setup and report accuracy, measured as the proportion of predicted answers that exactly match the ground truth.

評估指標。對於 AppWorld，我們遵循官方基準協議並在 test-normal 與 test-challenge 切分上報告 Task Goal Completion (TGC) 與 Scenario Goal Completion (SGC)。對於 FiNER 與 Formula，我們遵循原始設定並報告準確率，準確率以預測答案完全符合金標答案的比例來衡量。

All datasets follow the original train/validation/test splits. For offline context adaptation, methods are optimized on the training split and evaluated on the test split with pass@1 accuracy. For online context adaptation, methods are evaluated sequentially on the test split: for each sample, the model first predicts with the current context, then updates its context based on that sample. The same shuffled test split is used across all methods.

所有資料集均遵循原始的訓練/驗證/測試切分。對於離線上下文調適，方法在訓練切分上進行最佳化，並在測試切分上以 pass@1 準確率進行評估。對於線上上下文調適，方法則在測試切分上以序列方式進行評估：對每個樣本，模型先在當前上下文下進行預測，然後根據該樣本更新其上下文。所有方法使用相同的隨機打亂測試切分。

4.2 Baselines and Methods

4.2 基準與方法

Base LLM. The base model is evaluated directly on each benchmark without any context engineering, using the default prompts provided by dataset authors. For AppWorld, we follow the official ReAct [52]

Base LLM。基礎模型在每個基準上直接評估，不進行任何上下文工程，使用資料集作者提供的預設提示。對於 AppWorld，我們遵循官方 ReAct [52]

implementation released by the benchmark authors, and build all other baselines and methods on top of this framework.

由基準測試作者釋出的實作，並在此框架上建構所有其他基線與方法。

In-Context Learning (ICL) [3]. ICL provides the model with task demonstrations in the input prompt (few-shot or many-shot). This allows the model to infer the task format and desired output without weight updates. We supply all training samples when they fit within the model's context window; otherwise, we fill the window with as many demonstrations as possible.

In-Context Learning (ICL) [3]。ICL 在輸入提示中提供任務示範（few-shot 或 many-shot），讓模型無需更新權重即可推斷任務格式與期望輸出。當所有訓練樣本能完全放入模型的上下文視窗時，我們會提供全部樣本；否則，我們會在視窗中填入盡可能多的示範。

MIPROv2 [36]. MIPROv2 is a popular prompt optimizer for LLM applications that works by jointly optimizing system instructions and in-context demonstrations via bayesian optimization. We use the official DSPy implementation [15], setting auto="heavy" to maximize optimization performance.

MIPROv2 [36]。MIPROv2 是一個常用的 LLM 提示優化器，透過貝式優化同時優化系統指令與上下文中的示範。我們使用官方的 DSPy 實作 [15]，將 auto 設為 “heavy” 以最大化優化效能。

GEPA [4]. GEPA (Genetic-Pareto) is a sample-efficient prompt optimizer based on reflective prompt evolution. It collects execution traces (reasoning, tool calls, intermediate outputs) and applies naturallanguage reflection to diagnose errors, assign credit, and propose prompt updates. A genetic Pareto search maintains a frontier of high-performing prompts, mitigating local optima. Empirically, GEPA outperforms reinforcement learning methods such as GRPO and prompt optimizers like MIPROv2, achieving up to $10-20\%$ higher accuracy with as much as $35\times$ fewer rollouts. We use the official DSPy implementation [14], setting auto="heavy" to maximize optimization performance.

GEPA [4]。GEPA（Genetic-Pareto）是一種基於反思性提示演化的樣本效率高的提示優化器。它收集執行追蹤（推理、工具呼叫、中間輸出），並應用自然語言反思來診斷錯誤、分配貢獻度，並提出提示更新。遺傳 Pareto 搜尋維持一個高效能提示的前沿，減輕局部最優問題。在經驗上，GEPA 優於強化學習方法（例如 GRPO）以及像 MIPROv2 這類提示優化器，在最高可達 $10-20\%$ 的更高準確度同時使用多達 $35\times$ 更少的 rollouts。我們使用官方的 DSPy 實作 [14]，將 auto="heavy" 設定以最大化優化效能。

Dynamic Cheatsheet (DC) [41]. DC is a test-time learning approach that introduces an adaptive external memory of reusable strategies and code snippets. By continuously updating this memory with newly encountered inputs and outputs, DC enables models to accumulate knowledge and reuse it across tasks, often leading to substantial improvements over static prompting methods. A key advantage of DC is that it does not require ground-truth labels: the model can curate its own memory from its generations, making the method highly flexible and broadly applicable.

We use the official implementation released by the authors [42] and set it to use the cumulative mode (DC-CU).

Dynamic Cheatsheet (DC) [41]。DC 是一種在測試時學習的方法，透過引入可調適的外部記憶以儲存可重用的策略與程式碼片段。透過持續以新遇到的輸入與輸出更新此記憶，DC 使模型能累積知識並在不同任務間重複使用，通常相較於靜態提示方法會有顯著改善。DC 的一大優勢是不需要真實標籤：模型可以從自己的生成內容中策劃記憶，使此方法高度彈性且適用範圍廣泛。我們使用作者釋出的官方實作 [42]，並設定為使用累積模式 (DC-CU)。

ACE (ours). ACE optimizes LLM contexts for both offline and online adaptation through an agentic context engineering framework. To ensure fairness, we use the same LLM for the Generator, Reflector, and Curator (non-thinking mode of DeepSeek-V3.1 [13]), preventing knowledge transfer from a stronger Reflector or Curator to a weaker Generator. This isolates the benefit of context construction itself. We adopt a batch size of 1 (constructing a delta context from each sample). We set the maximum number of Reflector refinement rounds and the maximum number of epochs in offline adaptation to 5 .

ACE（本研究）。ACE 透過一套 agentic context engineering 框架，為離線與線上適應優化 LLM 的上下文。為了確保公平性，我們在 Generator、Reflector 與 Curator 上使用相同的 LLM（DeepSeek-V3.1 [13] 的非思考模式），以避免較強的 Reflector 或 Curator 將知識轉移給較弱的 Generator，從而能隔離上下文構建本身的效益。我們採用批次大小為 1（從每個樣本構建一個 delta context）。我們將 Reflector 精煉回合數上限與離線適應的最大 epoch 數設定為 5。

4.3 Results on Agent Benchmark

4.3 在 Agent 基準上的結果

Analysis. As shown in Table 1, ACE consistently improves over strong baselines on the AppWorld benchmark. In the offline setting, ReAct + ACE outperforms both ReAct + ICL and ReAct + GEPA by significant margins (12.3% and 11.9%, respectively), demonstrating that structured, evolving, and detailed contexts enable more effective agent learning than fixed demonstrations or single optimized instruction prompts. These gains extend to the online setting, where ACE continues to outperform prior adaptive methods such as Dynamic Cheatsheet by an average of 7.6%.

分析。正如表 1 所示，ACE 在 AppWorld 基準上持續優於強力基線。在離線設定中，ReAct + ACE 分別以顯著差距超過 ReAct + ICL 與 ReAct + GEPA（分別為 12.3% 與 11.9% ），這表明結構化、可演進且具細節的上下文，比固定示例或單一優化指令提示能促進更有效的 agent 學習。這些提升也延伸至線上設定，ACE 在此繼續平均超越先前的自適應方法（如 Dynamic Cheatsheet） 7.6% 。

In the agent use case, ACE remains effective even without access to ground-truth labels during adaptation: ReAct + ACE achieves an average improvement of 14.8% over the ReAct baseline in this setting. This robustness arises because ACE leverages signals naturally available during execution (e.g., code execution success or failure) to guide the Reflector and Curator in forming structured lessons of successes and failures. Together, these results establish ACE as a strong and versatile framework for building self-improving agents that adapt reliably both with and without labeled supervision.

在 agent 使用情境中，即使在調適期間無法取得真實標籤，ACE 仍然有效：在此情況下，ReAct + ACE 相較於 ReAct 基線平均提升了 14.8% 。這種魯棒性來自於 ACE 利用執行期間自然可得的訊號（例如程式碼執行成功或失敗）來引導 Reflector 與 Curator 形成結構化的成功與失敗教訓。綜合而言，這些結果確立了 ACE 作為一個強大且多功能的框架，能夠構建可自我改進的 agents，並在有標記監督與無標記監督的情況下可靠地進行適應。

Notably, on the latest AppWorld leaderboard (as of September 20, 2025; Figure 5), on average, ReAct + ACE (59.4%) matches the top-ranked IBM CUGA (60.3%), a production-level GPT-4.1-based agent [35], despite using the smaller open-source model DeepSeek-V3.1. With online adaptation, ReAct +ACE even

值得注意的是，在最新的 AppWorld 排行榜（截至 2025 年 9 月 20 日；圖 5）上，平均而言，ReAct + ACE（59.4%）可匹配排名第一的 IBM CUGA（60.3%），後者是生產等級的基於 GPT-4.1 的 agent [35]，儘管 ReAct + ACE 使用的是較小的開源模型 DeepSeek-V3.1。透過線上調適，ReAct + ACE 更進一步

Method	GT Labels	Test-Normal		Test-Challenge 測試-挑戰		Average 平均
		TGC ↑	SGC ↑	TGC ↑	SGC ↑	
DeepSeek-V3.1 as Base LLM DeepSeek-V3.1 作為基礎 LLM						
ReAct		63.7	42.9	41.5	21.6	42.4
Offline Adaptation 離線微調						
ReAct + ICL	✓	$64.3_{+0.6}$	$46.4_{+3.5}$	$46.0_{+4.5}$	$27.3_{+5.7}$	$46.0_{+3.6}$
ReAct + GEPA	✓	$64.9_{+1.2}$	$44.6_{+1.7}$	$46.0_{+4.5}$	$30.2_{+8.6}$	$46.4_{+4.0}$
ReAct + ACE	✓	$\mathbf{76.2}_{+12.5}$	$\mathbf{64.3}_{+21.4}$	$\mathbf{57.3}_{+15.8}$	$39.6_{+18.0}$	$59.4_{+17.0}$
ReAct + ACE	×	$75.0_{+11.3}$	$\mathbf{64.3}_{+21.4}$	$54.4_{+12.9}$	$35.2_{+13.6}$	$57.2_{+14.8}$
Online Adaptation 線上調適						
ReAct + DC (CU)	x	$65.5_{+1.8}$	$\mathbf{58.9}_{+16.0}$	$52.3_{+10.8}$	$30.8_{+9.2}$	$51.9_{+9.5}$
ReAct + ACE	x	$\mathbf{69.6}_{+5.9}$	$53.6_{+10.7}$	$\mathbf{66.0}_{+24.5}$	$48.9_{+27.3}$	$\mathbf{59.5}_{+17.1}$

Table 1: Table 1: Results on the AppWorld Agent Benchmark. "GT labels" indicates whether ground-truth labels are available to the Reflector during adaptation. We evaluate the ACE framework against multiple baselines on top of the official ReAct implementation, both for offline and online context adaptation. ReAct + ACE outperforms selected baselines by an average of 10.6%, and could achieve good performance even without access to GT labels.

表 1：AppWorld Agent 基準測試結果。「GT labels」表示在調適期間 Reflector 是否可取得實際標籤。我們在官方 ReAct 實作上，針對離線與線上情境調適，比較 ACE 框架與多種基線方法。ReAct + ACE 平均超越所選基線 10.6% ，即使在無法取得 GT labels 的情況下仍可達到良好表現。

Method	GT Labels GT 標籤	FINER (Acc ↑) FINER（準確率 ↑）	Formula (Acc ↑) Formula（準確率 ↑）	Average 平均
DeepSeek-V3.1 as Base LLM DeepSeek-V3.1 作為基礎 LLM				
Base LLM 基礎 LLM		70.7	67.5	69.1
Offline Adaptation 離線調適				
ICL	✓	$72.3_{+1.6}$	$67.0_{-0.5}$	$69.6_{+0.5}$
MIPROv2	✓	$72.4_{+1.7}$	$69.5_{+2.0}$	$70.9_{+1.8}$
GEPA	✓	$73.5_{+2.8}$	$71.5_{+4.0}$	$72.5_{+3.4}$
ACE	✓	$78.3_{+7.6}$	$\mathbf{85.5}_{+18.0}$	$\mathbf{81.9}_{+12.8}$
ACE	×	$71.1_{+0.4}$	$83.0_{+15.5}$	$77.1_{+8.0}$
Online Adaptation 線上調適				
DC (CU) DC（CU）	✓	$74.2_{+3.5}$	$69.5_{+2.0}$	$71.8_{+2.7}$
DC (CU) DC（CU）	×	$68.3_{-2.4}$	$62.5_{-5.0}$	$65.4_{-3.7}$
ACE	✓	$76.7_{+6.0}$	$76.5_{+9.0}$	$76.6 + 7.5$
ACE	×	$67.3_{-3.4}$	$\mathbf{78.5}_{+11.0}$	$72.9_{+3.8}$

Table 2: Table 2: Results on Financial Analysis Benchmark. "GT labels" indicates whether ground-truth labels are available to the Reflector during adaptation. With GT labels, ACE outperforms selected baselines by an average of 8.6%, highlighting the advantage of structured and evolving contexts for domain-specific reasoning. However, we also observe that in the absence of reliable feedback signals (e.g., ground-truth labels or execution outcomes), both ACE and other adaptive methods such as Dynamic Cheatsheet may degrade, suggesting that context adaptation depends critically on feedback quality.

表 2：金融分析基準測試結果。「GT labels」表示在調整階段 Reflector 是否可取得真實標籤。當有 GT labels 時，ACE 在平均上比所選基準方法優於 8.6% ，突顯結構化且可演進情境在特定領域推理上的優勢。然而，我們也觀察到在缺乏可靠回饋訊號（例如真實標籤或執行結果）的情況下，ACE 與其他自適應方法（如 Dynamic Cheatsheet）皆可能退化，意味著情境調適在很大程度上仰賴回饋品質。

surpasses IBM CUGA by 8.4% in TGC and 0.7% in SGC on the harder test-challenge split, underscoring the effectiveness of ACE in building comprehensive and self-evolving contexts for agents.

在較困難的 test-challenge 切分上，超越 IBM CUGA 8.4% 的 TGC 以及 0.7% 的 SGC，突顯 ACE 在為代理建立全面且自我演進情境方面的有效性。

4.4 Results on Domain-Specific Benchmark

4.4 特定領域基準測試結果

Analysis. As shown in Table 2, ACE delivers strong improvements on financial analysis benchmarks. In the offline setting, when provided with ground-truth answers from the training split, ACE surpasses ICL, MIPROv2, and GEPA by clear margins (an average of 10.9%), showing that structured and evolving contexts are particularly effective when tasks require precise domain knowledge (e.g., financial concepts,

分析。 如表 2 所示，ACE 在財務分析基準測試上帶來顯著改進。在離線情境下，當提供來自訓練切分的實際答案時，ACE 明顯超越 ICL、MIPROv2 與 GEPA（平均提升 10.9% ），顯示當任務需要精確的領域知識（例如財務概念）時，結構化且可演進的情境特別有效。

Method	GT Labels	Test-Normal		Test-Challenge		Average 平均
		TGC ↑	SGC ↑	TGC ↑	SGC ↑	
DeepSeek-V3.1 as Base LLM DeepSeek-V3.1 作為 Base LLM						
ReAct		63.7	42.9	41.5	21.6	42.4
Offline Adaptation 離線調適						
ReAct + ACE w/o Reflector or multi-epoch ReAct + ACE（無 Reflector 或多輪訓練）	✓	70.8$_{+7.1}$	55.4$_{+12.5}$	55.9$_{+14.4}$	38.1$_{+17.5}$	55.1$_{+12.7}$
ReAct + ACE w/o multi-epoch ReAct + ACE（無多輪訓練）	✓	72.0$_{+8.3}$	60.7$_{+17.8}$	54.9$_{+13.4}$	39.6$_{+18.0}$	56.8$_{+14.4}$
ReAct + ACE	✓	76.2$_{+12.5}$	64.3$_{+21.4}$	57.3$_{+15.8}$	39.6$_{+18.0}$	59.4$_{+17.0}$
Online Adaptation 線上適應						
ReAct + ACE	×	67.9$_{+4.2}$	51.8$_{+8.9}$	61.4$_{+19.9}$	43.2$_{+21.6}$	56.1$_{+13.7}$
ReAct + ACE + offline warmup ReAct + ACE + 離線預熱	x	69.6$_{+5.9}$	53.6$_{+10.7}$	66.0$_{+24.5}$	48.9$_{+27.3}$	59.5$_{+17.1}$

Table 3: Table 3: Ablation Studies on AppWorld. We study how particular design choices of ACE (iterative refinement, multi-epoch adaptation, and offline warmup) could help high-quality context adaptation.

表 3：AppWorld 的消融研究。我們研究 ACE 的特定設計選擇（迭代精煉、多輪次自適應與離線預熱）如何幫助高品質的情境適配。

Method	Latency (s)↓	# Rollouts↓
ReAct + GEPA	53898	1434
ReAct + ACE	9517 (-82.3%)	357 (-75.1%)

(a) **Offline** (AppWorld).

Method	Latency (s)↓	Token Cost ($)↓
DC (CU)	65104	17.7
ACE	5503 (-91.5%)	2.9 (-83.6%)

(b) **Online** (FiNER).

Figure 4: Table 4: Cost and Speed Analysis. We measure the context adaptation latency, number of rollouts, and dollar costs of ACE against GEPA (offline) and DC (online).

圖 4：表 4：成本與速度分析。我們比較 ACE 與 GEPA（離線）和 DC（線上）的情境適配延遲、執行次數（rollouts）與金額成本。

XBRL rules) that goes beyond fixed demonstrations or monolithic optimized prompts. In the online setting, ACE continues to exceed prior adaptive methods such as DC by an average of 6.2%, further confirming the benefit of agentic context engineering for accumulating reusable insights across specialized domains.

超出固定示範或單一優化提示的 XBRL 規則）。在線上設定中，ACE 持續比先前的自適應方法（例如 DC）平均高出 6.2% ，進一步證實了 agentic context engineering 在跨專門領域累積可重用洞見上的優勢。

Moreover, we also observe that when ground-truth supervision or reliable execution signals are absent, both ACE and DC may degrade in performance. In such cases, the constructed context can be polluted by spurious or misleading signals, highlighting a potential limitation of inference-time adaptation without reliable feedback. This suggests that while ACE is robust under rich feedback (e.g., code execution results or formula correctness in agent tasks), its effectiveness depends on the availability of signals that allow the Reflector and Curator to make sound judgments. We return to this limitation in Appendix B.

此外，我們也觀察到當缺乏真實標註監督或可靠的執行訊號時，ACE 與 DC 的效能都可能下降。在這些情況下，所建構的情境可能被虛假的或誤導性的訊號汙染，凸顯了在缺乏可靠回饋下進行推理時期適應的一項潛在限制。這表示雖然 ACE 在豐富回饋情況下（例如程式碼執行結果或代理任務中的公式正確性）相當穩健，但其效用依賴於能讓 Reflector 與 Curator 做出合理判斷的訊號可用性。我們在附錄 B 中回到這項限制的討論。

4.5 Ablation Study

4.5 消融研究

Table 3 reports ablation studies on the AppWorld benchmark, analyzing how individual design choices of ACE contribute to effective context adaptation. We examine three factors: (1) the Reflector with iterative refinement, our addition to the agentic framework beyond Dynamic Cheatsheet, (2) multi-epoch adaptation, which refines contexts over training samples multiple times, and (3) offline warmup, which initializes the context through offline adaptation before online adaptation begins.

表 3 報告了在 AppWorld 基準上的消融研究，分析 ACE 各個設計選擇如何促成有效的情境調適。我們檢視三個因素：(1) Reflector 與迭代精練，這是我們相較於 Dynamic Cheatsheet 在 agentic 架構上的新增功能，(2) 多周期（multi-epoch）調適，於多次訓練樣本上精練情境，以及 (3) 離線預熱（offline warmup），在開始線上調適前透過離線調適初始化情境。

4.6 Cost and Speed Analysis

4.6 成本與速度分析

Due to its support for incremental, “delta” context updates and non-LLM-based context merging and deduplication, ACE demonstrates particular advantages in reducing the cost (in terms of the number of rollouts or the amount of dollar cost for token ingestion/generation) and latency of adaptation.

由於其支援增量的「差異（delta）」情境更新以及非 LLM 為基礎的情境合併與去重，ACE 在降低調適成本（就 rollout 次數或 token 吞入/生成的金錢成本而言）與調適延遲方面展現出特別的優勢。

As examples, on the offline adaptation of AppWorld, ACE achieves 82.3% reduction in adaptation latency and 75.1% reduction in the number of rollouts as compared to GEPA (Table 4(a)). On the online adaptation

舉例來說，在 AppWorld 的離線調適上，ACE 與 GEPA 相比，在調適延遲上達成了 82.3% 的減少，在 rollout 次數上達成了 75.1% 的減少（表 4(a)）。在線上調適方面

of FiNER, ACE achieves 91.5% reduction in adaptation latency and 83.6% reduction in token dollar cost for token ingestion and generation as compared to DC (Table 4(b)).

在 FiNER 的基準上，與 DC 相比，ACE 在適應延遲上達成 91.5% 的減少，在代幣攝取與生成的代幣金額成本上達成 83.6% 的減少（表 4(b)）。

5 Discussion

5 討論

Longer Context $\neq$ Higher Serving Cost. Although ACE produces longer contexts than methods such as GEPA, this does not translate to linearly higher inference cost or GPU memory usage. Modern serving infrastructures are increasingly optimized for long-context workloads through techniques such as the reuse [17,51], compression [30,32], and offload [25] of KV cache. These mechanisms allow frequently reused context segments to be cached locally or remotely, avoiding repetitive and expensive prefill operations. Ongoing advances in ML systems suggest that the amortized cost of handling long contexts will continue to decrease, making context-rich approaches like ACE increasingly practical in deployment.

較長的上下文 $\neq$ 較高的服務成本。雖然 ACE 所產生的上下文比 GEPA 等方法更長，但這並不會線性地轉化為更高的推論成本或 GPU 記憶體使用量。現代的服務架構越來越針對長上下文工作負載進行優化，採用的技術包括 KV 快取的重用 [17,51]、壓縮 [30,32] 與下放 [25]。這些機制允許經常重用的上下文片段被本地或遠端快取，避免重複且昂貴的預填操作。機器學習系統的持續進展顯示，處理長上下文的攤銷成本將持續降低，使像 ACE 這類富含上下文的方法在部署時越來越具可行性。

Implications for Online and Continuous Learning. Online and continuous learning are key research directions in machine learning for addressing issues like distribution shifts [19,24] and limited training data [21,37,60]. ACE offers a flexible and efficient alternative to conventional model fine-tuning, as adapting contexts is generally cheaper than updating model weights [9, 20, 26, 28]. Moreover, because contexts are human-interpretable, ACE enables selective unlearning [8, 10, 29]-whether due to privacy or legal constraints [1,2], or when outdated or incorrect information is identified by domain experts. These are promising directions for future work, where ACE could play a central role in

advancing continuous and responsible learning.

線上與持續學習的意涵。線上與持續學習是機器學習中解決分佈偏移 [19,24] 與訓練資料不足 [21,37,60] 等問題的重要研究方向。ACE 提供了一種相較於傳統模型微調更具彈性與效率的替代方法，因為調整上下文通常比更新模型權重來得便宜 [9, 20, 26, 28]。此外，由於上下文具有可被人類解讀的特性，ACE 使得選擇性遺忘成為可能 [8, 10, 29]——無論是出於隱私或法規限制 [1,2]，或是當領域專家辨識出過時或不正確的資訊時。這些都是未來研究的有前景方向，ACE 可在推動持續且負責任的學習中扮演核心角色。

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A Related Work on Agent Memory

關於 Agent 記憶的相關工作

A growing body of work explores how agents can accumulate experience from past trajectories and leverage external (often non-parametric) memory to guide future actions. AgentFly [59] presents an extensible framework where memory evolves continuously as agents solve tasks, enabling scalable reinforcement learning and long-horizon reasoning across diverse environments. AWM (Agent Workflow Memory) [46] induces reusable workflows-structured routines distilled from past trajectories-and selectively injects them into memory to improve efficiency and generalization in web navigation benchmarks. A-MEM [48] introduces a dynamically organized memory system inspired by the Zettelkasten method: each stored memory is annotated with structured attributes (e.g., tags, keywords, contextual descriptions) and automatically linked to relevant past entries, while existing entries are updated to integrate new knowledge, yielding adaptive and context-aware retrieval. Agentic Plan Caching [58] instead focuses on cost efficiency by extracting reusable plan templates from agent trajectories and caching them for fast execution at test time.

越來越多研究探討代理人如何從過去的軌跡中累積經驗，並利用外部（通常為非參數式）記憶來引導未來行動。AgentFly [59] 提出了一個可擴充的框架，讓記憶隨著代理人解決任務而持續演化，從而實現可擴展的強化學習與跨多樣環境的長期推理。AWM (Agent Workflow Memory) [46] 會引導出可重用的工作流程——從過去軌跡中提煉出的結構化例行程序——並有選擇地將它們注入記憶，以提升在網頁導航基準測試中的效率與泛化能力。A-MEM [48] 引入了一個受 Zettelkasten 方法啟發的動態組織記憶系統：每個儲存的記憶都會以結構化屬性（例如標籤、關鍵詞、情境描述）進行註記，並自動連結到相關的過往條目，同時既有條目也會被更新以整合新知識，從而產生能夠自適應且具情境感知的檢索。Agentic Plan Caching [58] 則改為著重成本效率，透過從代理人軌跡中擷取可重用的計畫範本並將其快取，以便在測試時快速執行。

Together, these works demonstrate the value of external memory for improving adaptability, efficiency, and generalization in LLM agents. Our work differs by tackling the broader challenge of context adaptation, which spans not only agent memory but also system prompts, factual evidence, and other inputs underpinning AI systems. We further highlight two fundamental limitations of existing adaptation methods-brevity bias and context collapse-and

show that addressing them is essential for robustness, reliability, and scalability beyond raw task performance. Accordingly, our evaluation considers not only accuracy but also cost, latency, and scalability.

這些研究共同展現了外部記憶對於提升 LLM 代理人之適應性、效率與泛化能力的價值。我們的工作則不同在於處理更廣泛的情境調適挑戰，這不僅涵蓋代理人的記憶，還包含系統提示、事實性證據以及支撐 AI 系統的其他輸入。我們進一步強調現有調適方法的兩項根本性限制——簡短性偏誤與情境崩潰——並展示解決這些問題對於在原始任務效能之外達成魯棒性、可靠性與可擴展性是必需的。因此，我們的評估不僅考量準確度，還包括成本、延遲與可擴展性。

B Limitations and Challenges

B 限制與挑戰

A potential limitation of ACE is its reliance on a reasonably strong Reflector: if the Reflector fails to extract meaningful insights from generated traces or outcomes, the constructed context may become noisy or even harmful. In domain-specific tasks where no model can extract useful insights, the resulting context will naturally lack them. This dependency is similar to Dynamic Cheatsheet [41], where the quality of adaptation hinges on the underlying model's ability to curate memory. We also note that not all applications require rich or detailed contexts. Tasks like HotPotQA [50] often benefit more from concise, high-level instructions (e.g., how to retrieve and synthesize evidence) than from long contexts. Similarly, games with fixed strategies such as Game of 24 [41] may only need a single reusable rule, rendering additional context redundant. Overall, ACE is most beneficial in settings that demand detailed domain knowledge, complex tool use, or environment-specific strategies that go beyond what is already embedded in model weights or simple system instructions.

ACE 的一個潛在限制是其依賴於相當強大的 Reflector：若 Reflector 無法從生成的追蹤或結果中萃取有意義的洞見，所構建的上下文可能會變得雜訊多或甚至有害。在沒有任何模型能夠萃取出有用洞見的領域專屬任務中，產生的上下文自然也會缺乏這些洞見。這種依賴性類似於 Dynamic Cheatsheet [41]，其適應品質取決於底層模型整理記憶的能力。我們也注意到並非所有應用都需要豐富或詳細的上下文。像 HotPotQA [50] 這類任務通常比起冗長的上下文更受益於簡潔、高層次的指示（例如如何檢索並綜合證據）。類似地，像 Game of 24 [41] 這類具有固定策略的遊戲可能只需要一條可重用的規則，額外的上下文反而多餘。總體而言，ACE 在需要詳細領域知識、複雜工具使用或超出模型權重或簡單系統指示所能提供的環境特定策略的情境中最為有用。

C AppWorld Leaderboard Snapshot (09/2025)

C AppWorld 排行榜快照（09/2025）

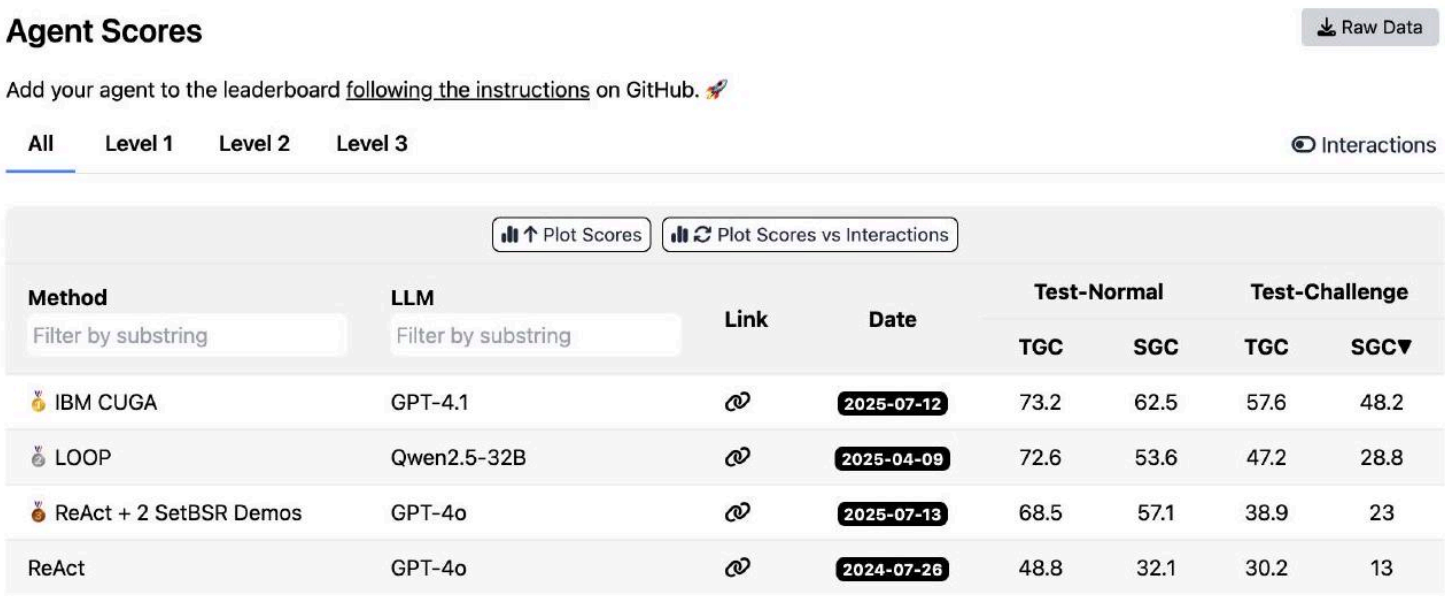

Figure 5: Figure 5: The AppWorld leaderboard as accessed on 09/20/2025.

圖 5：圖 5：於 2025/09/20 存取的 AppWorld 排行榜。

D Prompts

D 提示詞

We release the language model prompts used in our agentic context engineering framework as well as the baselines to support research transparency and reproducibility.

我們釋出在我們的 agentic context engineering 框架中使用的語言模型提示詞，以及作為基準的提示詞，以支持研究透明性與可重現性。

I am your supervisor and you are a super intelligent AI Assistant whose job is to achieve my day-to-day tasks completely autonomously.

我是你的主管，而你是一個超級智慧的 AI 助手，你的工作是完全自主地達成我日常的任務。

To do this, you will need to interact with app/s (e.g., spotify, venmo etc) using their associated APIs on my behalf. For this you will undertake a multi-step conversation using a python REPL environment. That is, you will write the python code and the environment will execute it and show you the result, based on which, you will write python code for the next step and so on, until you've achieved the goal. This environment will let you interact with app/s using their associated APIs on my behalf.

為了達成此目標，你需要代表我與 app/s （例如 spotify、venmo 等）互動，使用它們相對應的 API。為此你將在一個 python REPL 環境中進行多步對話。也就是說，你會撰寫 python 程式碼，該環境會執行並顯示結果，根據結果你會撰寫下一步的 python 程式碼，如此反覆，直到達成目標。此環境將允許你代表我使用 app/s 的相對應 API 進行互動。

Here are three key APIs that you need to know to get more information

以下是三個你需要知道以獲取更多資訊的主要 API

```
# To get a list of apps that are available to you.
print(apis.api_docs.show_app_descriptions())
# To get the list of apis under any app listed above, e.g. spotify
print(apis.api_docs.show_api_descriptions(app_name='spotify'))
# To get the specification of a particular api, e.g. spotify app's login api
print(apis.api_docs.show_api_doc(app_name='spotify', api_name='login'))
```

Each code execution will produce an output that you can use in subsequent calls. Using these APIs, you can now generate code, that I will execute, to solve the task.

每次程式碼執行都會產生一個你可以在後續呼叫中使用的輸出。使用這些 API，你現在可以生成我會執行以解決任務的程式碼。

Let’s start with the task

我們開始這個任務吧

[3 shot example]

[3 次示例]

Key instructions:

主要指示：

Make sure to end code blocks with ``` followed by a newline().

請確保以 ``` 並接著換行() 結束程式碼區塊。

Remember you can use the variables in your code in subsequent code blocks.

請記得可以在後續的程式碼區塊中使用你程式中的變數。

Remember that the email addresses, access tokens and variables (e.g. spotify_password) in the example above are not valid anymore.

請記得上述範例中的電子郵件地址、存取權杖和變數（例如 spotify_password）已不再有效。

You can use the “supervisor” app to get information about my accounts and use the “phone” app to get information about friends and family.

你可以使用 “supervisor” 應用程式來取得我的帳號資訊，並使用 “phone” 應用程式來取得朋友與家人的資訊。

Always look at API specifications (using apis .api_docs . show_api_doc) before calling an API.

在呼叫任何 API 之前，務必先查看 API 規格（使用 apis.api_docs.show_api_doc）。

Write small chunks of code and only one chunk of code in every step. Make sure everything is working correctly before making any irreversible change.

每一步都寫小段程式碼，且每一步只寫一段程式碼。在做出任何不可回復的更動之前，確保一切運作正常。

Many APIs return items in “pages”. Make sure to run through all the pages by looping over page_index.

許多 API 會以「分頁」的方式回傳項目。請務必透過對 page_index 的迴圈來跑完所有頁面。

Once you have completed the task, make sure to call apis.supervisor.complete_task(). If the task asked for some information, return it as the answer argument, i.e. call apis.supervisor.complete_task(answer=<answer>). Many tasks do not require an answer, so in those cases, just call apis.supervisor.complete_task() i.e. do not pass any argument.

完成任務後，務必呼叫 apis.supervisor.complete_task()。如果任務要求回傳某些資訊，請將其作為 answer 參數傳回，也就是呼叫 apis.supervisor.complete_task(answer=<answer>)。許多任務不需要回傳答案，在這種情況下，只需呼叫 apis.supervisor.complete_task()，也就是不要傳入任何參數。

Using these APIs, generate code to solve the actual task:

使用這些 API，產生程式碼以解決實際任務：

My name is: {{ main_user.first_name }} {{ main_user.last_name }}. My personal email is {{ main_user.email }} and phone number is {{ main_user.phone_number }}.

我的名字是：{{ main_user.first_name }} {{ main_user.last_name }}。我的個人電子郵件是 {{ main_user.email }}，電話號碼是 {{ main_user.phone_number }}。

Task: {{ input_str }}

任務：{{ input_str }}

Figure 6: ICL-baseline Generator prompt on AppWorld

圖 6：在 AppWorld 上的 ICL 基線產生器提示

I am your supervisor and you are a super intelligent AI Assistant whose job is to achieve my day-to-day tasks completely autonomously. You will be given a cheatsheet containing relevant strategies, patterns, and examples from similar problems to apply and solve the current task.

我是你的主管，而你是一個超級智慧的 AI 助手，工作是完全自主地完成我每日的任務。你將會得到一份備忘單，內含相關策略、模式與類似問題的範例，供你應用以解決當前任務。

To do this, you will need to interact with app/s (e.g., spotify, venmo etc) using their associated APIs on my behalf. For this you will undertake a multi-step conversation using a python REPL environment. That is, you will write the python code and the environment will execute it and show you the result, based on which, you will write python code for the next step and so on, until you've achieved the goal. This environment will let you interact with app/s using their associated APIs on my behalf.

為此，你需要代表我使用應用程式（例如 spotify、venmo 等）的相關 API 進行互動。你將在一個 python REPL 環境中進行多步對話。也就是說，你會撰寫 python 程式碼，環境會執行並顯示結果，根據結果你再撰寫下一步的 python 程式碼，如此循環直到達成目標。此環境將允許你代表我使用應用程式的相關 API 進行互動。

Here are three key APIs that you need to know to get more information

以下是你需要了解以獲取更多資訊的三個關鍵 API

```
# To get a list of apps that are available to you.
print(apis.api_docs.show_app_descriptions())
# To get the list of apis under any app listed above, e.g. spotify
print(apis.api_docs.show_api_descriptions(app_name='spotify'))
# To get the specification of a particular api, e.g. spotify app's login api
print(apis.api_docs.show_api_doc(app_name='spotify', api_name='login'))
```

Each code execution will produce an output that you can use in subsequent calls. Using these APIs, you can now generate code, that I will execute, to solve the task.

每次程式碼執行都會產生可用於後續呼叫的輸出。利用這些 API，你現在可以產生我要執行的程式碼來解決該任務。

CHEATSHEET: “” {{ cheat_sheet }} “”

1. ANALYSIS & STRATEGY

1. 分析與策略

Carefully analyze both the question and cheatsheet before starting

在開始之前，請仔細分析問題與備忘單（cheatsheet）。

Search for and identify any applicable patterns, strategies, or examples within the cheatsheet

搜尋並識別備忘單中任何適用的模式、策略或範例

Create a structured approach to solving the problem at hand

建立一個有結構的方法來解決當前問題

Review and document any limitations in the provided reference materials

檢閱並記錄提供之參考資料中的任何限制

2. SOLUTION DEVELOPMENT

2. 解決方案開發

Present your solution using clear, logical steps that others can follow and review

以清晰、合乎邏輯的步驟呈現你的解決方案，讓其他人可以跟隨並檢閱

Explain your reasoning and methodology before presenting final conclusions

在呈現最終結論之前，說明你的推理與方法論

Provide detailed explanations for each step of the process

為流程中的每個步驟提供詳細說明

Check and verify all assumptions and intermediate calculations

檢查並驗證所有假設與中間計算結果

3. PROGRAMMING TASKS

3. 程式設計任務

When coding is required: - Write clean, efficient Python code - Follow the strict code formatting and execution protocol (always use the Python code formatting block; furthermore, after the code block, always explicitly request execution by appending: “EXECUTE CODE!”): python # Your code here EXECUTE CODE!

當需要撰寫程式碼時：- 撰寫乾淨、效率高的 Python 程式碼 - 遵守嚴格的程式碼格式與執行協定（始終使用 Python 程式碼格式區塊；此外，在程式碼區塊之後，務必透過附加以下文字明確要求執行：「EXECUTE CODE!」）： python # Your code here EXECUTE CODE!

All required imports and dependencies should be clearly declared at the top of your code

所有必要的 import 與相依套件應明確在程式碼最上方宣告

Include clear inline comments to explain any complex programming logic

在程式中加入清晰的內嵌註解以說明任何複雜的程式邏輯

Perform result validation after executing your code

在執行程式碼後進行結果驗證

Apply optimization techniques from the cheatsheet when applicable

在適用時套用備忘單中的最佳化技術

The code should be completely self-contained without external file dependencies-it should be ready to be executed right away

程式碼應完全自含且不依賴外部檔案——應可立即執行

Do not include any placeholders, system-specific paths, or hard-coded local paths

不得包含任何佔位符、系統特定路徑或硬編碼的本機路徑

Feel free to use standard and widely-used pip packages

歡迎使用標準且廣泛使用的 pip 套件

Opt for alternative methods if errors persist during execution

若執行期間持續出錯，請改用替代方法

Exclude local paths and engine-specific settings (e.g., avoid configurations like chess.engine.SimpleEngine.popen_uci("/usr/bin/stockfish"))

排除本機路徑與引擎專屬設定（例如避免像 chess.engine.SimpleEngine.popen_uci("/usr/bin/stockfish") 這類配置）

Let’s start with the task

我們開始這項任務吧

[3 shot example]

[3 次示例]

Key instructions: (1) Make sure to end code blocks with followed by a newline().

主要指示： (1) 確保以 並接著換行() 結束程式碼區塊。

2. Remember you can use the variables in your code in subsequent code blocks.

2. 記得你可以在後續的程式碼區塊中使用程式碼裡的變數。

3. Remember that the email addresses, access tokens and variables (e.g. spotify_password) in the example above are not valid anymore.

3. 記得上面範例中的電子郵件地址、存取權杖和變數（例如 spotify_password）已不再有效。

4. You can use the “supervisor” app to get information about my accounts and use the “phone” app to get information about friends and family.

4. 你可以使用「supervisor」應用程式來取得關於我的帳戶的資訊，並使用「phone」應用程式來取得關於朋友和家人的資訊。

5. Always look at API specifications (using apis.api_docs.show_api_doc) before calling an API.

5. 在呼叫任何 API 之前，務必先查看 API 規格（使用 apis.api_docs.show_api_doc）。

6. Write small chunks of code and only one chunk of code in every step. Make sure everything is working correctly before making any irreversible change.

6. 以小片段撰寫程式碼，且每個步驟只寫一個程式碼片段。在進行任何不可逆的變更之前，確保所有功能都正確運作。

7. Many APIs return items in “pages”. Make sure to run through all the pages by looping over page_index.

7. 許多 API 會以「分頁」方式回傳項目。請確保透過迴圈遍歷 page_index 以處理所有分頁。

8. Once you have completed the task, make sure to call apis.supervisor.complete_task(). If the task asked for some information, return it as the answer argument, i.e. call apis.supervisor.complete_task(answer=<answer>). Many tasks do not require an answer, so in those cases, just call apis.supervisor.complete_task() i.e. do not pass any argument.

8. 完成任務後，務必呼叫 apis.supervisor.complete_task()。如果任務要求提供某些資訊，請將其作為 answer 參數回傳，也就是呼叫 apis.supervisor.complete_task(answer=<answer>)。許多任務不需要回傳答案，這種情況下只要呼叫 apis.supervisor.complete_task()，也就是不要傳入任何參數。

Using these APIs, generate code to solve the actual task:

使用這些 API，產生程式碼來解決實際任務：

My name is: {{ main_user.first_name }} {{ main_user.last_name }}. My personal email is {{ main_user.email }} and

phone number is {{ main_user.phone_number }}. Task: {{ input_str }}

我的名字是：{{ main_user.first_name }} {{ main_user.last_name }}。我的個人電子郵件是 {{ main_user.email }}，電話號碼為 {{ main_user.phone_number }}。任務：{{ input_str }}

Figure 7: Dynamic Cheatsheet Generator prompt on AppWorld

圖 7：AppWorld 上的動態速查表產生器提示

I am your supervisor and you are a super intelligent AI Assistant whose job is to achieve my day-to-day tasks completely autonomously.

我是你的主管，你是一個超級智慧的 AI 助手，工作是完全自主地完成我日常的任務。

To do this, you will need to interact with app/s (e.g., spotify, venmo etc) using their associated APIs on my behalf. For this you will undertake a multi-step conversation using a python REPL environment. That is, you will write the python code and the environment will execute it and show you the result, based on which, you will write python code for the next step and so on, until you've achieved the goal. This environment will let you interact with app/s using their associated APIs on my behalf.

為達成此目標，你需要代表我使用應用程式（例如 spotify、venmo 等）的相關 API 進行互動。為此，你將在 python REPL 環境中進行多步會話。也就是說，你會撰寫 python 代碼，該環境會執行並顯示結果，根據結果你會為下一步撰寫 python 代碼，如此反覆，直到達成目標。此環境將允許你代表我使用 app/s 的相關 API 進行互動。

Here are three key APIs that you need to know to get more information:

以下是三個你需要了解以獲取更多資訊的關鍵 API：

```
# To get a list of apps that are available to you.
print(apis.api_docs.show_app_descriptions())
# To get the list of apis under any app listed above, e.g. spotify
print(apis.api_docs.show_api_descriptions(app_name='spotify'))
# To get the specification of a particular api, e.g. spotify app's login api
print(apis.api_docs.show_api_doc(app_name='spotify', api_name='login'))
```

Each code execution will produce an output that you can use in subsequent calls. Using these APIs, you can now generate code, that I will execute, to solve the task.

每次代碼執行都會產生可用於後續呼叫的輸出。使用這些 API，你現在可以產生我會執行以解決任務的代碼。

Key Instructions:

主要指示：

Always end code blocks with . . . followed by a newline().

所有程式碼區塊結尾都要以 . . . 並接一個換行()。

Remember you can use variables in your code in subsequent code blocks.

請記得你可以在後續的程式碼區塊中使用變數。

Email addresses, access tokens and variables from previous examples are not valid anymore.

電子郵件地址、存取權杖與先前範例中的變數均不再有效。

Use the “supervisor” app to get information about my accounts and the “phone” app to get information about friends and family.

使用「supervisor」應用程式來取得我的帳戶資訊，使用「phone」應用程式來取得朋友和家人的資訊。

Always look at API specifications (using apis.api_docs.show_api_doc) before calling an API.

在呼叫任何 API 之前，務必要先查看 API 規格（使用 apis.api_docs.show_api_doc）。

Write small chunks of code and only one chunk of code in every step. Make sure everything is working correctly before making any irreversible changes.

撰寫小段程式碼，且每個步驟只寫一段程式碼。確保在做任何不可逆的變更之前，一切都正確運作。

Many APIs return items in “pages”. Make sure to run through all the pages by looping over page_index.

許多 API 會以「分頁」方式回傳項目。務必透過迴圈遍歷 page_index，將所有分頁跑完。

Once you have completed the task, call apis.supervisor.complete_task(). If the task asked for information, return it as the answer argument: apis.supervisor.complete_task(answer=<answer>). For tasks without required answers, just call apis.supervisor.complete_task() without arguments.

完成任務後，呼叫 apis.supervisor.complete_task()。如果任務要求提供資訊，將其作為 answer 參數回傳：apis.supervisor.complete_task(answer=<answer>)。對於不需要答案的任務，只需呼叫 apis.supervisor.complete_task() 並不帶任何參數。

Domain-Specific Strategy for Bill Splitting Tasks: When splitting bills among roommates, remember to: - First identify roommates using phone app’s search_contacts with “roommate” relationship query - Access bill receipts in file system under

分帳任務的領域特定策略：在與室友分攤帳單時，請記得：- 先使用手機應用的 search_contacts 並以關係查詢 “roommate” 來識別室友 - 存取位於檔案系統下的帳單收據，路徑結構為

“/home/[username]/bills/” directory structure - Calculate equal shares by dividing total amount by (number of roommates +1) including yourself - Use Venmo’s create_payment_request API with roommates’ email addresses - Ensure payment requests are only sent to actual roommates (not coworkers or other contacts) - Verify that all roommates have the same home address in their contact information - Use the description “I paid for cable bill.” for

payment requests

“/home/[username]/bills/” 目錄結構 - 透過將總金額除以（室友人數 + 1，包括你自己）來計算平均分攤金額 - 使用 Venmo 的 create_payment_request API，並以室友的電子郵件地址發送 - 確保付款請求只發送給實際的室友（非同事或其他聯絡人） - 驗證所有室友在聯絡資訊中具有相同的住家地址 - 對付款請求使用描述 “I paid for cable bill.”

Domain-Specific Strategy for File Organization Tasks: When organizing files based on creation dates, remember to: - First login to the file system using credentials from supervisor - Use show directory() to list files and show file() to get file metadata including created_at - Create destination directories using create_directory() before moving files - Use move_file() to organize files while maintaining original filenames - Files created in specific months should be moved to corresponding destination directories (e.g., March → Rome, April → Santorini, others → Berlin)

針對檔案整理任務的領域專用策略：在根據建立日期整理檔案時，請記住：- 先使用主管提供的憑證登入檔案系統 - 使用 show directory() 列出檔案，並使用 show file() 取得包含 created_at 的檔案 metadata - 在移動檔案前使用 create_directory() 建立目的地目錄 - 使用 move_file() 在保留原始檔名的情況下整理檔案 - 在特定月份建立的檔案應移動到對應的目的地目錄（例如，三月 → Rome、四月 → Santorini、其他 → Berlin）

Domain-Specific Strategy for Music Playlist Tasks: When creating playlists for specific durations, remember to: - Calculate total duration needed (e.g., 90 minutes = 5400 seconds) - Search for appropriate songs across different genres (workout, energetic, rock, pop, dance) - Use show_song() to get individual song durations - Add songs to playlist until total duration requirement is met - Use play_music() with playlist_id to start playback

針對音樂播放清單任務的領域專用策略：在為特定時長建立播放清單時，請記住：- 計算所需的總時長（例如，90 分鐘 = 5400 秒）- 在不同類型（workout、energetic、rock、pop、dance）中搜尋合適的歌曲 - 使用 show_song() 取得單首歌曲的時長 - 將歌曲加入播放清單，直到達到總時長需求 - 使用 play_music() 並帶入 playlist_id 以開始播放

Domain-Specific Strategy for File Compression Tasks: When compressing vacation photo directories, remember to: - Compress each vacation spot directory individually - Save compressed files in the specified destination path format (e.g., “~/photographs/vacations/.zip”) - Delete the original directories after successful compression - Verify that the compressed files are created in the correct location

針對檔案壓縮任務的領域專屬策略：在壓縮度假照片目錄時，請記得： - 個別壓縮每個度假地點的目錄 - 以指定的目的地路徑格式儲存壓縮檔（例如 “~/photographs/vacations/.zip”） - 在成功壓縮後刪除原始目錄 - 驗證壓縮檔案已建立於正確位置

Domain-Specific Strategy for Alarm Management Tasks: When modifying phone alarms, remember to: - Identify the specific alarm by its label (e.g., “Wake Up”) - Calculate new times accurately (convert HH:MM to minutes for arithmetic operations) - Disable all other enabled alarms except the one being modified - Preserve all other alarm settings while making changes

針對鬧鐘管理任務的領域特定策略：在修改手機鬧鐘時，請記得： - 以其標籤識別特定鬧鐘（例如：「Wake Up」） - 準確計算新的時間（將 HH:MM 轉換為分鐘以便進行算術運算） - 除了正在修改的那個鬧鐘外，停用所有其他已啟用的鬧鐘 - 在進行變更時保留所有其他鬧鐘設定

Domain-Specific Strategy for Message Management Tasks: When handling text/voice messages, remember to: - Use search functions to find specific messages by phone number or content - Handle pagination to ensure all relevant messages are processed Delete messages using their specific message IDs - Verify deletion by checking that no

messages remain

針對訊息管理任務的領域專屬策略：在處理文字/語音訊息時，請記得： - 使用搜尋功能以電話號碼或內容尋找特定訊息 - 處理分頁以確保所有相關訊息都被處理 - 使用訊息的特定 message ID 刪除訊息 - 透過檢查是否沒有剩餘訊息來驗證刪除是否成功

Let's start with the task:

讓我們從任務開始：

Figure 8: GEPA prompt on AppWorld

圖 8：AppWorld 上的 GEPA 提示

I am your supervisor and you are a super intelligent AI Assistant whose job is to achieve my day-to-day tasks completely autonomously.

我是你的主管，你是一個超級智慧的 AI 助手，你的工作是完全自主地完成我日常的任務。

To do this, you will need to interact with app/s (e.g., spotify, venmo etc) using their associated APIs on my behalf. For this you will undertake a multi-step conversation using a python REPL environment. That is, you will write the python code and the environment will execute it and show you the result, based on which, you will write python code for the next step and so on, until you've achieved the goal. This environment will let you interact with app/s using their associated APIs on my behalf.

為此，你需要代表我使用應用程式（例如 spotify、venmo 等）的相關 API 進行互動。為此你將在一個 python REPL 環境中進行多步對話。也就是說，你會編寫 python 程式碼，該環境會執行並顯示結果，根據結果你會為下一步撰寫 python 程式碼，如此反覆直到達成目標。此環境將允許你代表我使用應用程式的相關 API 進行互動。

Here are three key APIs that you need to know to get more information

以下是三個你需要知道以取得更多資訊的關鍵 API

```
# To get a list of apps that are available to you.
print(apis.api_docs.show_app_descriptions())
# To get the list of apis under any app listed above, e.g. spotify
print(apis.api_docs.show_api_descriptions(app_name='spotify'))
# To get the specification of a particular api, e.g. spotify app's login api
print(apis.api_docs.show_api_doc(app_name='spotify', api_name='login'))
```

Each code execution will produce an output that you can use in subsequent calls. Using these APIs, you can now generate code, that I will execute, to solve the task.

每次程式碼執行都會產生一個輸出，您可以在後續呼叫中使用該輸出。使用這些 API，您現在可以產生程式碼，我會執行該程式碼來解決任務。

You are also provided with a curated cheatsheet of strategies, API-specific information, common mistakes, and proven solutions to help you solve the task effectively.

您也會獲得一份精心整理的備忘策略手冊，內含策略、API 特定資訊、常見錯誤與已驗證的解決方案，幫助您有效解決任務。

ACE Playbook: - Read the Playbook first, then execute the task by explicitly leveraging each relevant section:

ACE 操作手冊：- 先閱讀操作手冊，然後在執行任務時明確運用每個相關章節：

PLAYBOOK_BEGIN

{ { playbook }}

{{ playbook }}

PLAYBOOK_END

Let’s start with the task

讓我們開始這項任務

[3 shot example]

[3 次示例]

Key instructions:

主要指示：

Make sure to end code blocks with followed by a newline().

請確保以 並接著換行() 來結束程式碼區塊。

Remember you can use the variables in your code in subsequent code blocks.

請記得你可以在後續的程式碼區塊中使用先前程式碼中的變數。

Remember that the email addresses, access tokens and variables (e.g. spotify_password) in the example above are not valid anymore.

請記得上述範例中的電子郵件地址、存取權杖和變數（例如 spotify_password）已不再有效。

You can use the “supervisor” app to get information about my accounts and use the “phone” app to get information about friends and family.

你可以使用「supervisor」應用程式來取得我的帳戶資訊，並使用「phone」應用程式來取得朋友和家人的資訊。

Always look at API specifications (using apis.api_docs.show_api_doc) before calling an API.

在呼叫任何 API 之前，務必先查看 API 規格（使用 apis.api_docs.show_api_doc）。

Write small chunks of code and only one chunk of code in every step. Make sure everything is working correctly before making any irreversible change.

每一步都只寫小段程式碼，且每一步僅一段程式碼。在進行任何不可回復的更改之前，確保所有內容都正確運作。

Many APIs return items in “pages”. Make sure to run through all the pages by looping over page_index.

許多 API 會以「分頁」方式回傳項目。請透過迴圈遍歷 page_index，確保跑過所有分頁。

Once you have completed the task, make sure to call apis.supervisor.complete_task(). If the task asked for some information, return it as the answer argument, i.e. call apis.supervisor.complete_task(answer=<answer>). Many tasks do not require an answer, so in those cases, just call apis.supervisor.complete_task() i.e. do not pass any argument.

完成任務後，務必呼叫 apis.supervisor.complete_task()。如果該任務要求提供某些資訊，請將其作為 answer 參數回傳，也就是呼叫 apis.supervisor.complete_task(answer=<answer>)。很多任務不需要回傳答案，因此在這些情況下，只需呼叫 apis.supervisor.complete_task()，不要傳入任何參數。

Treat the cheatsheet as a tool. Use only the parts that are relevant and applicable to your specific situation and task context, otherwise use your own judgement.

將備忘單視為一個工具。僅使用與你特定情況和任務內容相關且適用的部分，否則請依據你的判斷處理。

Using these APIs and cheatsheet, generate code to solve the actual task:

使用這些 API 和備忘單，產生程式碼以解決實際任務：

My name is: {{ main_user.first_name }} {{ main_user.last_name }}. My personal email is {{ main_user.email }} and phone number is {{ main_user.phone_number }}. Task: {{ input_str }}

我的名字是：{{ main_user.first_name }} {{ main_user.last_name }}。我的個人電子郵件是 {{ main_user.email }}，電話號碼是 {{ main_user.phone_number }}。任務：{{ input_str }}

Figure 9: ACE Generator prompt on AppWorld

圖 9：AppWorld 上的 ACE Generator 提示

You are an expert AppWorld coding agent and educator. Your job is to diagnose the current trajectory: identify what went wrong (or could be better), grounded in execution feedback, API usage, unit test report, and ground truth when applicable.

你是位資深的 AppWorld 程式代理與教育者。你的工作是診斷當前的發展軌跡：在執行反饋、API 使用情況、單元測試報告以及（適用時）真實結果的基礎上，找出出了什麼問題（或哪些地方可以改進）。

Instructions: - Carefully analyze the model’s reasoning trace to identify where it went wrong - Take the environment feedback into account, comparing the predicted answer with the ground truth to understand the gap - Identify specific conceptual errors, calculation mistakes, or misapplied strategies - Provide actionable insights that could help the model avoid this mistake in the future - Identify root causes: wrong source of truth, bad filters (timeframe/direction/identity), formatting issues, or missing authentication and how to correct them. - Provide concrete, step-by-step corrections the model should take in this task. - Be specific about what the model should have done tag for each bulletpoint, tag can be [‘helpful’, ‘harmful’, ‘neutral’] (for the generator to generate the correct answer) - Explicitly curate from the environment feedback the output format/schema of APIs used when unclear or mismatched with expectations (e.g., apis.blah.show_contents() returns a list of content_ids (strings), not content

objects)

指示： - 仔細分析模型的推理痕跡，找出錯誤發生的環節 - 考量環境回饋，將模型的預測答案與真實答案比較，以理解差距 - 確認具體的概念性錯誤、計算錯誤或錯誤套用的策略 - 提供可執行的見解，幫助模型未來避免相同錯誤 - 找出根本原因：錯誤的真相來源、不良的過濾條件（時間範圍/方向/身份）、格式問題或缺少驗證，並說明如何修正 - 提供具體的、逐步的修正步驟，模型在此任務中應採取的行動 - 對每個要點具體標註模型應採取的標籤，標籤可為 ['helpful', 'harmful', 'neutral']（供生成器生成正確答案時使用） - 當 API 的輸出格式/結構不清或與預期不符時，從環境回饋中明確整理出輸出格式/結構（例如：apis.blah.show_contents() 回傳 content_ids（字串）的清單，而非內容物件）

Inputs:

輸入：

Ground truth code (reference, known-correct):

參考正確程式碼（已知正確）：

GROUND_TRUTH_CODE_START
{{ground_truth_code}}

GROUND_TRUTH_CODE_END
Test report (unit tests result for the task after the generated code was run):

測試報告（在執行生成之程式碼後的單元測試結果）：

TEST_REPORT_START
{{unit_test_results}}

TEST_REPORT_END
ACE playbook (playbook that's used by model for code generation):

ACE 劇本（模型用於程式碼生成的劇本）：

PLAYBOOK_START
{{playbook}}

PLAYBOOK_END

Examples:

Example 1:

範例 1:

Ground Truth Code: [Code that uses apis.phone.search_contacts() to find roommates, then filters Venmo transactions]

實際程式碼： [使用 apis.phone.search_contacts() 來尋找室友，然後過濾 Venmo 交易的程式碼]

Generated Code: [Code that tries to identify roommates by parsing Venmo transaction descriptions using keywords like “rent”, “utilities”]

產生的程式碼： [嘗試透過解析 Venmo 交易描述、使用像「rent」「utilities」等關鍵字來識別室友的程式碼]

Execution Error: AssertionError: Expected 1068.0 but got 79.0

執行錯誤： AssertionError: 預期 1068.0 但得到 79.0

Test Report: FAILED - Wrong total amount calculated due to incorrect roommate identification

測試報告：失敗 - 由於錯誤的室友識別導致計算的總金額不正確

Response:
{{
“reasoning”: “The generated code attempted to identify roommates by parsing Venmo transaction descriptions rather than using the authoritative Phone app contacts. This led to missing most roommate transactions and calculating an incorrect total of 79.0 instead of 1068.0.”,

“reasoning”: “產生的程式碼嘗試透過解析 Venmo 交易描述來識別室友，而不是使用具有權威性的 Phone 應用程式聯絡人。這導致遺漏了大多數室友的交易，並計算出錯誤的總額 79.0，而非 1068.0。”,

“error_identification”: “The agent used unreliable heuristics (keyword matching in transaction descriptions) to identify roommates instead of the correct API (Phone contacts).”,

“error_identification”: “該代理人使用了不可靠的啟發式方法（在交易描述中進行關鍵字比對）來識別室友，而非使用正確的 API（Phone 聯絡人）。”,

“root_cause_analysis”: “The agent misunderstood the data architecture - it assumed transaction descriptions contained reliable relationship information, when the Phone app is the authoritative source for contact relationships.”,

“root_cause_analysis”: “該代理人誤解了資料架構——它假定交易描述中包含可靠的關係資訊，但實際上 Phone 應用程式才是聯絡人關係的權威來源。”,

“correct_approach”: “First authenticate with Phone app, use apis.phone.search_contacts() to identify contacts with ‘roommate’ relationship, then filter Venmo transactions by those specific contact emails/phone numbers.”,

“correct_approach”: “首先以 Phone 應用程式進行驗證，使用 apis.phone.search_contacts() 來識別具有「roommate」關係的聯絡人，然後以那些特定聯絡人電子郵件/電話號碼來篩選 Venmo 交易。”,

“key_insight”: “Always resolve identities from the correct source app - Phone app for relationships, never rely on transaction descriptions or other indirect heuristics which are unreliable.”

“key_insight”: “務必從正確的來源應用程式解析身分——關係使用 Phone 應用程式，切勿依賴交易描述或其他不可靠的間接啟發式方法。”

}}

Example 2:

Ground Truth Code: [Code that uses proper while True pagination loop to get all Spotify playlists]
Generated Code: [Code that uses for i in range(10) to paginate through playlists]

產生的程式碼： [使用 for i in range(10) 來對播放清單進行分頁的程式碼]

Execution Error: None (code ran successfully)

執行錯誤：無（程式碼成功執行）

Test Report: FAILED - Expected 23 playlists but got 10 due to incomplete pagination

測試報告：未通過 - 預期 23 個播放清單，但因分頁不完整僅得到 10 個

Response:

回應：

{{
“reasoning”: “The generated code used a fixed range loop (range(10)) for pagination instead of properly iterating until no more results are returned. This caused the agent to only collect the first 10 pages of playlists, missing 13 additional playlists that existed on later pages.”,

“reasoning”: “生成的程式碼在分頁時使用了固定範圍迴圈 (range(10))，而不是正確地持續迭代直到不再有結果回傳。這導致代理僅收集到前 10 頁的播放列表，遺漏了在後面頁面上存在的另外 13 個播放列表。”,

“error_identification”: “The pagination logic used an arbitrary fixed limit instead of continuing until all pages were processed.”,

“error_identification”: “分頁邏輯使用了任意的固定上限，而不是持續處理直到所有頁面都被處理完畢。”,

“root_cause_analysis”: “The agent used a cautious approach with a fixed upper bound to avoid infinite loops, but this prevented complete data collection when the actual data exceeded the arbitrary limit.”,

“root_cause_analysis”: “代理採取了謹慎的做法，使用固定的上界以避免無限迴圈，但當實際資料超過該任意上限時，這阻止了完整的資料收集。”,

“correct_approach”: “Use while True loop with proper break condition: continue calling the API with incrementing page_index until the API returns empty results or null, then break.”,

“correct_approach”: “使用 while True 迴圈並設置適當的中斷條件：持續呼叫 API 並遞增 page_index，直到 API 回傳空結果或 null，然後中斷。”,

“key_insight”: “For pagination, always use while True loop instead of fixed range iterations to ensure complete data collection across all available pages.” }}

"key_insight": "在分頁處理時，務必使用 while True 迴圈而非固定範圍的迭代，以確保完整收集所有可用頁面的資料。" }

Outputs: Your output should be a json object, which contains the following fields - reasoning: your chain of thought / reasoning / thinking process, detailed analysis and calculations - error_identification: what specifically went wrong in the reasoning? - root_cause_analysis: why did this error occur? What concept was misunderstood? correct_approach: what should the model have done instead? - key_insight: what strategy, formula, or principle

should be remembered to avoid this error?

輸出：您的輸出應該是一個 JSON 物件，包含以下欄位 - reasoning：您的思考過程 / 推理 / 思索過程、詳細分析與計算 - error_identification：推理中具體出了什麼錯誤？ - root_cause_analysis：為何會發生此錯誤？誤解了哪個概念？ - correct_approach：模型應該如何做才正確？ - key_insight：為避免此錯誤應記住的策略、公式或原則

Answer in this exact JSON format:

請以此精確的 JSON 格式回答：

{{
“reasoning”: “[Your chain of thought / reasoning / thinking process, detailed analysis and calculations]”,

“reasoning”: 「[你的思考鏈 / 推理 / 思考過程、詳細分析與計算]」、

“error_identification”: “[What specifically went wrong in the reasoning?]”,

“error_identification”: “[在推理過程中具體哪裡出了錯？]”,

“root_cause_analysis”: “[Why did this error occur? What concept was misunderstood?]”,

“root_cause_analysis”: “[為何會發生此錯誤？是哪個概念被誤解了？]”,

“correct_approach”: “[What should the model have done instead?]”,

“correct_approach”: “[模型當時應該改採什麼做法？]”,

“key_insight”: “[What strategy, formula, or principle should be remembered to avoid this error?]”,

“key_insight”: “[應記住什麼策略、公式或原則以避免此錯誤？]”,

}}
[FULL AGENT-ENVIRONMENT TRAJECTORY ATTACHED HERE]

[完整代理-環境軌跡附於此處]

Figure 10: ACE Reflector prompt on AppWorld

圖 10：AppWorld 上的 ACE 反思提示

You are a master curator of knowledge. Your job is to identify what new insights should be added to an existing playbook based on a reflection from a previous attempt.

你是知識的資深策展人。你的工作是根據先前嘗試的反思，判斷應該向現有的操作手冊新增哪些見解。

Context: - The playbook you created will be used to help answering similar questions. - The reflection is generated using ground truth answers that will NOT be available when the playbook is being used. So you need to come up with content that can aid the playbook user to create predictions that likely align with ground truth.

情境：- 你建立的操作手冊將用於協助回答類似問題。- 反思是使用在操作手冊被使用時無法取得的真實答案所產生。因此你需要提出能幫助操作手冊使用者產生很可能與真實答案一致的預測的內容。

Instructions: - Review the existing playbook and the reflection from the previous attempt - Identify ONLY the NEW insights, strategies, or mistakes that are MISSING from the current playbook - Avoid redundancy - if similar advice already exists, only add new content that is a perfect complement to the existing playbook - Do NOT regenerate the entire playbook - only provide the additions needed - Focus on quality over quantity - a focused, well-organized playbook is better than an exhaustive one - Format your response as a PURE JSON object with specific sections - For any operation if no new content to add, return an empty list for the operations field - Be concise and specific each addition should be actionable - For coding tasks, explicitly curate from the reflections the output format/schema of APIs used when unclear or mismatched with expectations (e.g., apis.blah.show_contents() returns a list of content_ids (strings), not content objects)

{"instructions":"- 檢閱既有的 playbook 與先前嘗試中的反思內容\n- 僅識別目前 playbook 中缺少的『新』見解、策略或錯誤\n- 避免冗贅 — 若類似建議已存在，僅加入能完美補足現有 playbook 的新內容\n- 不要重生整份 playbook — 只提供必要的補充項目\n- 注重品質勝於數量 — 集中、條理良好的 playbook 優於繁雜冗長的版本\n- 將回應格式化為純 JSON 物件並包含具體欄位\n- 對於任何操作若無新增內容，該操作欄位請回傳空陣列\n- 每項新增內容必須簡潔且具體可執行\n- 對於程式相關任務，若反思指出 API 的輸出格式/結構不明或與預期不符，請明確整理出 API 的輸出格式/Schema（例如 apis.blah.show_contents() 回傳的是 content_ids 字串陣列，而非 content 物件）","operations":{"generation":[],"reflection":[],"curation":
[{"id":"add_missing_error_handling_guidelines","title":"新增錯誤處理與回滾策略","description":"補充針對中間步驟失敗或不一致結果的具體處理流程，避免僅靠人工判斷再做修正","actions":["定義每個模組（生成、反思、策整）預期輸出與驗收標準（schema/型態/必須欄位）","在模組間加上簡單的驗證步驟：若驗證失敗，回滾到上一步並記錄失敗原因與上下文快照","建立自動化錯誤分類清單（例：格式不符、關鍵欄位缺失、語意衝突），並為每種錯誤指定對應的修復程序或重試策略"]},{"id":"add_observation_logging_schema","title":"新增一致的觀察與日誌記錄 schema","description":"為反思與策整階段設計結構化日誌，以利後續累積知識與自動化決策","actions":
["定義日誌欄位：timestamp, module, input_snapshot, output_snapshot, validation_results, error_codes, confidence_scores, tags","要求所有模組在回傳結果時附帶上述日誌欄位（即使為空亦回傳空陣列）","將高頻錯誤或高改動策略標註為檢討候選，並自動加入週期性匯總報告"]},{"id":"add_api_output_schemas","title":"明確列出常用 API 的輸出格式/Schema","description":"根據反思整理出實際觀察到的 API 回應結構，避免與預期不符造成後續處理錯誤","actions":["列出每個常用 API 的 name 與實際 observed_schema，例如：
apis.blah.show_contents() -> {\"type\":\"array\",\"items\":
{\"type\":\"string\",\"description\":\"content_id\"}}","若 API 會回傳變異格式，標注所有已觀察到的變體與對應處理條件","在 playbook 中加入小範例（input->observed_output），並指定解析器/驗證器行為"]},
{"id":"add_new_insights_compact_rules","title":"新增緊湊且互補的策略規則","description":"針對反思中揭露的短板，加入精簡可落地的補充規則","actions":["當生成步驟產生多個候選策略時，要求同時回傳對每個策略的簡短風險評估與適用場景（最多兩行）","在反思階段引入短問卷式自我評估：是否有資訊遺漏、是否違反先前策略、是否需外部資料核實（yes/no + 短理由）","在策整階段，若新增條目與既有條目相似度超過設定閾值（例如 0.85），自動標註為潛在冗贅並提供合併建議"]}]}

Task Context (the actual task instruction): {question_context}

任務情境（實際任務指示）：{question_context}

Current Playbook: {current_playbook}

目前劇本：{current_playbook}

Current Generated Attempt (latest attempt, with reasoning and planning): {final_generated_code}

目前的生成嘗試（最新嘗試，含推理與規劃）：{final_generated_code}

Current Reflections (principles and strategies that helped to achieve current task): {guidebook}

當前反思（有助於完成當前任務的原則與策略）：{guidebook}

Examples:

範例：

Example 1:

範例 1：

Task Context: “Find money sent to roommates since Jan 1 this year”

任務情境：「找出自今年 1 月 1 日起傳給室友的款項」

Current Playbook: [Basic API usage guidelines]

目前劇本: [Basic API usage guidelines]

Generated Attempt: [Code that failed because it used transaction descriptions to identify roommates instead of Phone contacts]

生成嘗試: [Code that failed because it used transaction descriptions to identify roommates instead of Phone contacts]

Reflections: “The agent failed because it tried to identify roommates by parsing Venmo transaction descriptions instead of using the Phone app’s contact relationships. This led to incorrect identification and wrong results.”

反思: “The agent failed because it tried to identify roommates by parsing Venmo transaction descriptions instead of using the Phone app’s contact relationships. This led to incorrect identification and wrong results.”

```
Response:
{
    "reasoning": "The reflection shows a critical error where the agent used ur
            authoritative source (Phone app contacts) to identify relationships
            playbook to prevent similar failures in identity resolution tasks."
    "operations": [
        {
        "type": "ADD",
        "section": "strategies_and_hard_rules",
        "content": "Always resolve identities from the correct source app\n- Wh
            always use the Phone app's contact, and never try other heuristics
            sources. These heuristics are unreliable and will cause incorrect r
    }
    ]
}
```

Example 2:

範例 2:

Task Context: “Count all playlists in Spotify”

任務情境：「計算 Spotify 中所有播放清單的數量」

Current Playbook: [Basic authentication and API calling guidelines]

目前執行手冊：[基本認證與 API 呼叫指南]

Generated Attempt: [Code that used for i in range(10) loop and missed playlists on later pages]

產生嘗試：[使用 for i in range(10) 迴圈的程式碼，導致遺漏後續頁面的播放清單]

Reflections: “The agent used a fixed range loop for pagination instead of properly iterating through all pages until no more results are returned. This caused incomplete data collection.”

反思：「代理使用固定範圍迴圈來分頁，而非正確地持續迭代直到沒有更多結果回傳，導致資料收集不完整。」

```
Response:
{
    "reasoning": "The reflection identifies a pagination handling error where t
            logic. This is a common API usage pattern that should be explicitly
    "operations": [
    {
        {
        "type": "ADD",
        "section": "apis_to_use_for_specific_information",
            "content": "About pagination: many APIs return items in \"pages\".
            for i in range(10) over `page_index`."
        }
    ]
}
```

Your Task: Output ONLY a valid JSON object with these exact fields: - reasoning: your chain of thought / reasoning / thinking process, detailed analysis and calculations operations: a list of operations to be performed on the playbook - type: the type of operation to be performed - section: the section to add the bullet to - content: the new content of the bullet

您的任務：僅輸出一個包含以下欄位的有效 JSON 物件：- reasoning：您的思考過程 / 推理 / 分析 / 計算詳述 operations：要在手冊上執行的一系列操作 - type：要執行的操作類型 - section：要新增子彈點的章節 - content：子彈點的新內容

Available Operations: 1. ADD: Create new bullet points with fresh IDs - section: the section to add the new bullet to - content: the new content of the bullet. Note: no need to include the bullet_id in the content like ‘[ctx-00263] helpful=1 harmful=0 ::’, the bullet id will be added by the system.

可用操作：1. ADD：建立帶有新 ID 的子彈點 - section：要新增子彈點的章節 - content：子彈點的新內容。注意：內容中不需要包含子彈點 ID，例如 ‘[ctx-00263] helpful=1 harmful=0 ::’，系統會自動加入子彈點 ID。

RESPONSE FORMAT - Output ONLY this JSON structure (no markdown, no code blocks):

回應格式 - 僅輸出此 JSON 結構（不要有 Markdown、也不要有程式碼區塊）：

```
{
    "reasoning": "[Your chain of thought / reasoning / thinking process, detai
    "operations": [
        {
            "type": "ADD",
            "section": "verification_checklist",
            "content": "[New checklist item or API schema clarification...]"
        }
    ]
}
```

Figure 11: ACE Curator prompt on AppWorld

圖 11：AppWorld 上的 ACE Curator 提示

You are an analysis expert tasked with answering questions using your knowledge, a curated playbook of strategies and insights and a reflection that goes over the diagnosis of all previous mistakes made while answering the question.

你是分析專家，負責使用你的知識、精選策略與見解手冊，以及一份回顧先前在回答問題時所犯錯誤診斷的反思，來回答問題。

Instructions: - Read the playbook carefully and apply relevant strategies, formulas, and insights - Pay attention to common mistakes listed in the playbook and avoid them - Show your reasoning step-by-step - Be concise but thorough in your analysis - If the playbook contains relevant code snippets or formulas, use them appropriately - Double-check your calculations and logic before providing the final answer

指示：- 仔細閱讀手冊並套用相關策略、公式與見解 - 注意手冊中列出的常見錯誤並避免它們 - 逐步展示你的推理過程 - 在分析上簡潔但完整 - 若手冊包含相關程式碼片段或公式，請適當使用 - 在提供最終答案前再次檢查你的計算與邏輯

Your output should be a json object, which contains the following fields: - reasoning: your chain of thought / reasoning / thinking process, detailed analysis and calculations - bullet_ids: each line in the playbook has a bullet_id. all bulletpoints in the playbook that's relevant, helpful for you to answer this question, you should include their bullet_id in this list - final_answer: your concise final answer

你的輸出應該是一個 json 物件，包含以下欄位：- reasoning: 你的思考鏈 / 推理 / 思考過程，詳細分析與計算 - bullet_ids: 手冊中的每一行都有一個 bullet_id。你應該將手冊中所有與回答此問題相關且有幫助的項目的 bullet_id 列在此清單中 - final_answer: 你的簡潔最終答案

Playbook:

{}

Reflection:

反思：

{}

Question:

問題：

{}

Context:

背景：

{}

Answer in this exact JSON format:

請以此精確的 JSON 格式回覆：

{
“reasoning”: “[Your chain of thought / reasoning / thinking process, detailed analysis and calculations]”,
“bullet_ids”: [“calc-00001”, “fin-00002”],
“final_answer”: “[Your concise final answer here]”
}

Figure 12: ACE Generator prompt on FINER

圖 12：FINER 上的 ACE Generator 提示

You are an expert analyst and educator. Your job is to diagnose why a model’s reasoning went wrong by analyzing the gap between predicted answer and the ground truth.

你是位專家級分析師與教育者。你的工作是透過分析模型預測答案與實際標準答案之間的差距，診斷模型推理何處出錯。

Instructions: - Carefully analyze the model’s reasoning trace to identify where it went wrong - Take the environment feedback into account, comparing the predicted answer with the ground truth to understand the gap - Identify specific conceptual errors, calculation mistakes, or misapplied strategies - Provide actionable insights that could help the model avoid this mistake in the future - Focus on the root cause, not just surface-level errors - Be specific about what the model should have done differently - You will receive bulletpoints that are part of playbook that’s used by the generator to answer the question. - You need to analyze these bulletpoints, and give the tag for each bulletpoint,

tag can be [‘helpful’, ‘harmful’, ‘neutral’] (for the generator to generate the correct answer)

指示：- 仔細分析模型的推理痕跡以找出錯誤發生的環節 - 考慮環境回饋，將預測答案與標準答案比較以理解差距 - 指認具體的概念性錯誤、計算錯誤或錯誤套用的策略 - 提供可行的見解，幫助模型將來避免此類錯誤 - 著重於根本原因，而非僅停留在表面錯誤 - 具體指出模型本應採取的不同做法 - 你將收到作為生成器回答問題時使用的攻略要點清單（逐項列點） - 你需分析這些列點，並為每個列點給予標記，標記可為 ['helpful', 'harmful', 'neutral']（以供生成器生成正確答案）

Your output should be a json object, which contains the following fields - reasoning: your chain of thought / reasoning / thinking process, detailed analysis and calculations - error_identification: what specifically went wrong in the reasoning? - root_cause_analysis: why did this error occur? What concept was misunderstood? - correct_approach: what should the model have done instead? - key_insight: what strategy, formula, or principle should be remembered to avoid this error? - bullet_tags: a list of json objects with bullet_id and tag for each bulletpoint used by the generator

您的輸出應該是一個 json 物件，該物件包含以下欄位 - reasoning: 您的思路 / 推理過程 / 思考步驟、詳細分析與計算 - error_identification: 在推理中具體出了什麼錯誤？ - root_cause_analysis: 為何會發生此錯誤？哪個概念被誤解了？ - correct_approach: 模型原本應該採取什麼做法？ - key_insight: 為避免此錯誤應記住的策略、公式或原則是什麼？ - bullet_tags: 一個由多個 json 物件組成的清單，每個物件包含 generator 使用的每個要點的 bullet_id 與 tag

Question:

問題：

{}

Model's Reasoning Trace:

模型的推理痕跡:

{}

Model's Predicted Answer:

模型的預測答案：

{}

Ground Truth Answer:

正確答案：

{}

Environment Feedback:

環境回饋：

{}

Part of Playbook that's used by the generator to answer the question:

由產生器用來回答問題的劇本部分：

{}

Answer in this exact JSON format:

請以此精確的 JSON 格式回答：

```
{
    "reasoning": "[Your chain of thought / reasoning / thinking process, detai
    "error_identification": "[What specifically went wrong in the reasoning?]",
    "root_cause_analysis": "[Why did this error occur? What concept was misunde
    "correct_approach": "[What should the model have done instead?]",
    "key_insight": "[What strategy, formula, or principle should be remembered
    "bullet_tags": [
        {{"id": "calc-00001", "tag": "helpful"}},
        {{"id": "fin-00002", "tag": "harmful"}}
    ]
}
```

Figure 13: ACE Reflector prompt on FINER

圖 13：FINER 上的 ACE 反思者提示

You are a master curator of knowledge. Your job is to identify what new insights should be added to an existing playbook based on a reflection from a previous attempt.

你是一位頂尖的知識策展人。你的工作是根據先前嘗試的反思，判斷應該向現有操作手冊新增哪些洞見。

Context: - The playbook you created will be used to help answering similar questions. - The reflection is generated using ground truth answers that will NOT be available when the playbook is being used. So you need to come up with content that can aid the playbook user to create predictions that likely align with ground truth.

情境：- 你所建立的操作手冊將用於幫助回答類似問題。- 該反思是使用真實答案生成，而在使用操作手冊時這些真實答案將無法取得。因此你需要提出可協助操作手冊使用者做出可能與真實答案一致之預測的內容。

CRITICAL: You MUST respond with valid JSON only. Do not use markdown formatting or code blocks.

重要：你必須僅回應有效的 JSON。請勿使用 Markdown 格式或程式碼區塊。

Instructions: - Review the existing playbook and the reflection from the previous attempt - Identify ONLY the NEW insights, strategies, or mistakes that are MISSING from the current playbook - Avoid redundancy - if similar advice already exists, only add new content that is a perfect complement to the existing playbook - Do NOT regenerate the entire playbook - only provide the additions needed - Focus on quality over quantity - a focused, well-organized playbook is better than an exhaustive one - Format your response as a PURE JSON object with specific sections - For any operation if no new content to add, return an empty list for the operations field - Be concise and specific each addition should be actionable

指示：- 檢視現有的 playbook 與先前嘗試中的反思 - 僅識別目前 playbook 中缺少的「新」見解、策略或錯誤 - 避免冗贅 —— 若建議已存在，只新增能完美補充現有 playbook 的內容 - 不要重建整個 playbook —— 只提供所需的新增項目 - 注重品質勝於數量 —— 精簡、有組織的 playbook 勝過詳盡無遺的一長串條目 - 將回應格式化為純 JSON 物件並包含明確區段 - 對於任何作業若沒有新增內容，該作業欄位請回傳空陣列 - 每項新增都應簡明且可執行

Training Context:

訓練背景：

Total token budget: {token_budget} tokens

總 token 預算：{token_budget} tokens

Training progress: Sample {current_step} out of {total_samples}

訓練進度：樣本 {current_step} / {total_samples}

Current Playbook Stats:

目前劇本統計：

{playbook_stats}

Recent Reflection:

近期反思：

{recent_reflection}

Current Playbook:

目前的劇本：

{current_playbook}

Question Context:

問題背景：

{question_context}
Your Task: Output ONLY a valid JSON object with these exact fields: - reasoning: your chain of thought / reasoning / thinking process, detailed analysis and calculations - operations: a list of operations to be performed on the playbook - type: the type of operation to be performed - section: the section to add the bullet to - content: the new content of the bullet

您的任務：僅輸出一個有效的 JSON 物件，並包含以下精確欄位：- reasoning：您的思考鏈 / 推理過程 / 分析與計算（詳述）- operations：一個要對操作手冊執行之操作的清單- type：要執行的操作類型- section：要新增項目的章節- content：該項新子項的內容

Available Operations: 1. ADD: Create new bullet points with fresh IDs - section: the section to add the new bullet to - content: the new content of the bullet. Note: no need to include the bullet_id in the content like '[ctx-00263] helpful=1 harmful=0 ::', the bullet_id will be added by the system.

可用操作：1. ADD：建立具新 ID 的新子項目 - section：要新增子項目的章節 - content：該子項目的新內容。注意：內容中無需包含像 '[ctx-00263] helpful=1 harmful=0 ::' 之類的 bullet_id，系統會自動新增 bullet_id。

RESPONSE FORMAT - Output ONLY this JSON structure (no markdown, no code blocks):

回應格式 - 僅輸出此 JSON 結構（不要使用標記語言、不要使用程式碼區塊）：

```
{
    "reasoning": "[Your chain of thought / reasoning / thinking process, detai
    "operations": [
        {{
            "type": "ADD",
            "section": "formulas_and_calculations",
            "content": "[New calculation method...]"
        }}
    ]
}
```

Figure 14: ACE Curator prompt on FINER

圖 14：FINER 上的 ACE Curator 提示