

Recursive Language Models

Alex L. Zhang¹ Tim Kraska¹ Omar Khattab¹

Abstract

We study allowing large language models (LLMs) to process arbitrarily long prompts through the lens of inference-time scaling. We propose **Recursive Language Models (RLMs)**, a general inference paradigm that treats long prompts as part of an external *environment* and allows the LLM to *programmatically* examine, decompose, and *recursively call itself over* snippets of the prompt. We find that RLMs can successfully process inputs up to two orders of magnitude beyond model context windows and, even for shorter prompts, dramatically outperform the quality of vanilla frontier LLMs and common long-context scaffolds across four diverse long-context tasks while having comparable cost. At a small scale, we post-train the first natively recursive language model. Our model, **RLM-Qwen3-8B**, outperforms the underlying Qwen3-8B model by 28.3% on average and even approaches the quality of vanilla GPT-5 on three long-context tasks. Code is available at <https://github.com/alexzhang13/rlm>.

1. Introduction

Frontier reasoning models have limited context windows and, even within their limits, tend to exhibit *context rot* (Hong et al., 2025), a phenomenon illustrated in Figure 1 where quality degrades steeply as prompts get longer. Though we expect context lengths to steadily rise through improvements to training, architecture, and infrastructure, we are interested in *whether it is possible to scale the context size of general-purpose LLMs by orders of magnitude*. This is increasingly urgent as LLMs begin to be widely adopted for long-horizon tasks, in which they must routinely process tens if not hundreds of millions of tokens.

We study this question through the lens of scaling inference-time compute. We are inspired by the way that *reasoning models* have become the fundamental interface to LLMs,

¹MIT CSAIL, Cambridge, MA, USA. Correspondence to: Alex L. Zhang, Omar Khattab <altzhang@mit.edu, okhattab@mit.edu>.

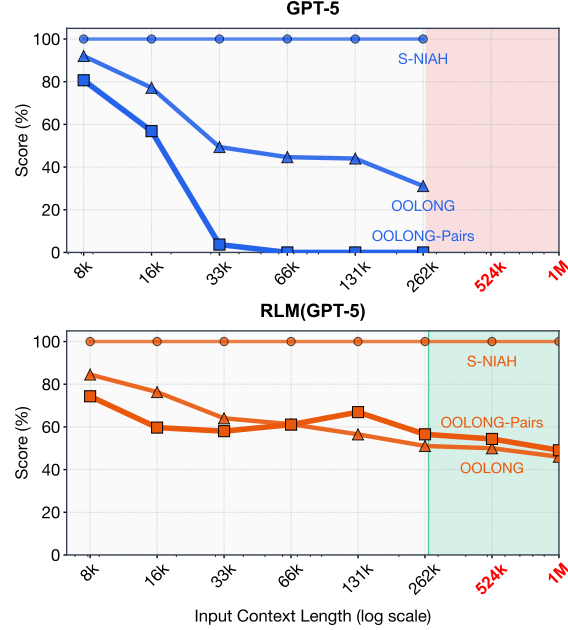


Figure 1. A comparison of GPT-5 and a corresponding RLM using GPT-5 on three long-context tasks of increasing complexity: **S-NIAH**, **OOLONG**, and **OOLONG-Pairs**. For each task, we scale the input length from 2^{13} to 2^{18} . GPT-5 performance degrades significantly as a function of both input length and task complexity, while the RLM maintains strong performance. Inputs beyond the red region do not fit in GPT-5’s context window of 272K tokens, but the RLM handles them effectively. Additional experiments across other models and benchmarks are in §3.

resulting not only in empirical gains but also additional theoretical expressive power (Merrill & Sabharwal, 2024) compared to vanilla Transformers. Though most inference-time methods for dealing with long context are task-specific (Wu et al., 2021; Chang et al., 2024), the most popular general approach is *context condensation* or *compaction* (Khattab et al., 2021; Smith, 2025; OpenAI, 2025b; Wu et al., 2025), where context from user requests or agent trajectories is repeatedly summarized once it exceeds a length threshold. Unfortunately, compaction is rarely expressive enough for tasks that require dense access throughout the prompt. It presumes that *some* details that appear early in the prompt can safely be forgotten to make room for new content.

We introduce **Recursive Language Models (RLMs)**, a general-purpose inference paradigm for dramatically scaling the effective input and output lengths of LLMs. The key

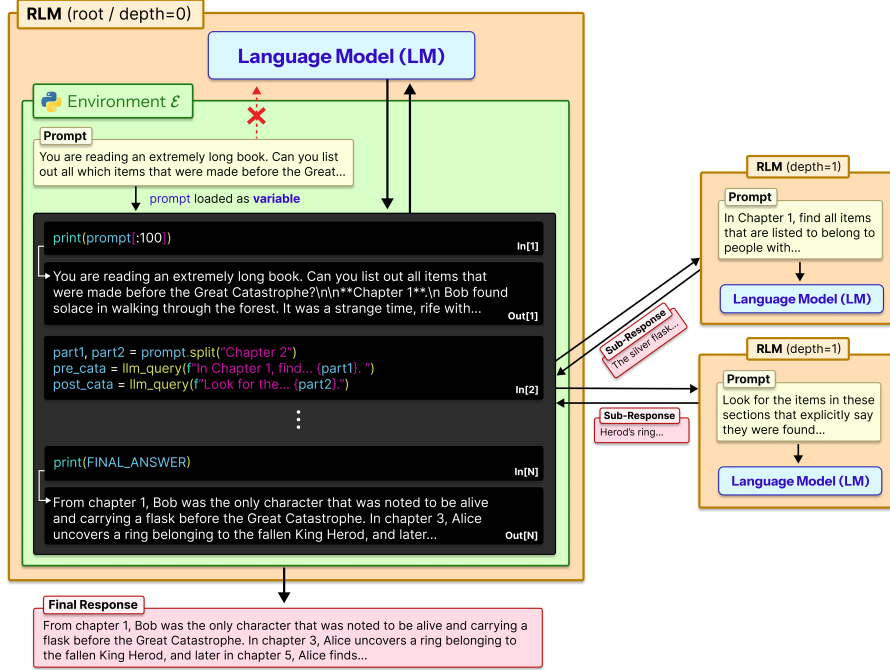


Figure 2. A Recursive Language Model (RLM) treats prompts as part of the environment. It loads the input prompt as a variable inside a REPL environment \mathcal{E} and writes code to peek into, decompose, and invoke itself recursively over programmatic snippets of the variable.

insight is that arbitrarily long user prompts should not be fed into the neural network (e.g., Transformer) directly but should instead be treated as *part of the environment that the LLM is tasked to symbolically and recursively interact with*.

As Figure 2 shows, an RLM exposes the same external interface as an LLM or a reasoning model: it accepts a string prompt of arbitrary structure and produces a string response. Given a prompt P , the RLM initializes a Read-Eval-Print Loop (REPL) programming environment in which P is set as the value of a variable. It then offers the LLM general context about the REPL environment (e.g., the length of the string P), and permits it to write code that peeks into and decomposes P , and to iteratively observe any side effects from execution. Crucially, RLMs encourage the LLM to understand, transform, and execute the input prompt by *writing symbolic programs that invoke the LLM itself* on as many slices of the input as necessary.

By treating the prompt itself as an external object and enabling symbolic recursion, RLMs tackle limitations of expressive power in recent work on coding agents, retrieval agents, and sub-agent delegation. In particular, prior coding agents and retrieval agents treat some designated external data source (e.g., a filesystem or a corpus of search documents) as an environment for fetching snippets. However, they *can only fill up the underlying LLM’s context window with snippets before breaking down*. Similarly, prior self-delegation approaches (Anthropic, 2025; Sentient AI, 2025; Schroeder et al., 2025; Sun et al., 2025) allow LLMs to invoke themselves as sub-agents. However, they are *hand-*

icapped by the underlying LLM’s limited output lengths because they are designed to verbalize sub-calls autoregressively rather than producing them programmatically.

We evaluate RLMs using a frontier closed model (GPT-5; Singh et al. 2025) and a frontier open model (Qwen3-Coder-480B-A35B; Qwen Team 2025b) across four tasks with varying levels of complexity: deep research (Chen et al., 2025), information aggregation (Bertsch et al., 2025), code repository understanding (Bai et al., 2025), and a synthetic pairwise reasoning task where even frontier models fail catastrophically. We compare RLMs against direct LLM calls as well as context compaction, retrieval tool-use agents, and code-generation agents.

We find that RLMs demonstrate extremely strong performance even at the 10M+ token scale, and substantially outperform all other approaches at long-context processing, in many cases by double-digit percentage gains while maintaining comparable cost. In particular, as demonstrated in Figure 1, RLMs exhibit far less severe degradation for longer contexts and more sophisticated tasks.

Finally, at a small scale, we post-train the first natively recursive language model, demonstrating that RLMs can be improved quickly with little additional training. While a small open model (Qwen3-8B; Yang et al. 2025) struggles to solve long context tasks even in an RLM scaffold, our simple general-purpose training recipe uses only 1,000 samples from unrelated domains to improve its performance by a median of 28.3% across the four evaluation tasks.

2. Recursive Language Models

Given a base neural language model \mathcal{M} with maximum context size K , a Recursive Language Model (RLM) is an inference-time scaffold around \mathcal{M} that treats the user prompt as part of the environment without giving up the ability to densely process its content through different calls to \mathcal{M} . Given an arbitrary-length prompt string $P \in \Sigma^*$, an RLM interacts with a persistent external environment \mathcal{E} and returns a response string $Y \in \Sigma^*$ (Figure 2). We would like effectively *unbounded input tokens* ($|P| \gg K$), *unbounded output tokens*, and an *unbounded semantic horizon*, e.g. the ability to do $\Omega(|P|)$ or $\Omega(|P|^2)$ semantic work.

Algorithm 1 describes how an RLM achieves this. Given a prompt P , the RLM initializes a persistent REPL programming environment with a variable containing the user prompt as a string and a function for invoking a sub-RLM with a new prompt. Then, it starts the RLM loop. In the first iteration, the algorithm invokes the *root* neural model \mathcal{M} with only (constant-size) metadata about the user prompt, like its length, a short prefix, and how to access parts of it.

The root is instructed via prompting (Appendix C) and/or fine-tuning (Appendix A) to operate like an RLM: that is, to *generate code that helps it understand and transform its parts of its prompt P* , and to build up intermediate values and the final response into new variables, potentially by *invoking the sub-RLM within loops*. In Section 4, we find that existing LLMs can be prompted to do this and that training an 8B model to be natively recursive is promising.

Each iteration of the RLM loop executes code in the REPL, updates REPL state (intermediate variables), and collects in `stdout` any printed text. Only (constant-size) metadata about `stdout`, like a short prefix and length, is appended to \mathcal{M} ’s history for the next iteration.¹ Once the RLM sets the variable `Final` inside the REPL, iteration stops and the value in `Final` is returned as the response.

RLMs make three simple design choices that are missing from existing scaffolds. To highlight these, we include Algorithm 2 to illustrate a deceptively “similar” algorithm that is far less expressive. Both algorithms support some notion of sub-calls, external objects, and code execution, but they differ in terms of where the prompt and intermediate values live and where recursion occurs.

First, an RLM must give the underlying LLM \mathcal{M} a *symbolic handle* to the user prompt P , so the model can manipulate it

¹This is key: it forces \mathcal{M} to rely on variables and sub-calls to manage long strings instead of polluting its window. In principle, if we trim each turn to c tokens, we will have at most K/c root iterations, each of which can launch arbitrarily many sub-calls. This is not a fundamental limitation, e.g. one could move the root horizon itself into a variable, but we typically want to limit the iterations at any level of recursion irrespective.

Algorithm 1 A recursive language model, around LLM \mathcal{M}

Input: prompt P

Output: response Y

```
state ← InitREPL(prompt=P)
state ← AddFunction(state, sub_RLM_M)
hist ← [Metadata(state)]
while True do
  code ← LLM_M(hist)
  (state, stdout) ← REPL(state, code)
  hist ← hist || code || Metadata(stdout)
  if state[Final] is set then
    return state[Final]
```

Algorithm 2 Alternate scaffold with standard (poor) design choices for prompts, sub-calls, and code execution

Input: prompt P

Output: response Y

```
actions ← {Finish, Exec, Search, sub_LLM_M}
hist ← [Metadata(actions), P] // Flaw #1
while True do
  (action, val) ← LLM_M(hist)
  if action is Finish then
    return val // Flaw #2
  out ← RUN(action, val) // Flaw #3
  hist ← hist || (action, val, out)
  if Tok(hist) > K then
    hist ← Compact(hist)
```

without copying text into the root context window. Instead, ineffective Algorithm 2 starts by putting the user prompt P into the LLM context window (`hist`) and thus inherits the window limitations of \mathcal{M} and falls back to heuristics like context compaction. Even though the scaffold can access external data with, say, a `Search` action or filesystem access, it is fatally bounded with respect to user input.

Second, ineffective Algorithm 2 asks \mathcal{M} to autoregressively generate the output directly, via a `Finish` action. This may seem innocuous, but it means that it also cannot generate longer outputs than the context window of \mathcal{M} permits.

Third, and perhaps most importantly, an RLM requires *symbolic recursion*. That is, code running *inside* \mathcal{E} must be able to invoke \mathcal{M} on programmatically constructed transformations of P (e.g., inside arbitrarily large loops), storing intermediate results symbolically. Though Algorithm 2 includes both a code execution action and a “sub-LLM” action separately, it is not able to invoke the sub-LLM programmatically and hence can only delegate a few *explicitly verbalized tasks* rather than writing short programs that can, say, loop over slices of the prompt and launch $\Omega(|P|)$ or even $\Omega(|P|^2)$ processes to understand or transform all parts of P .

3. Scaling Long Context Tasks

We hypothesize that the effective context window (Hsieh et al., 2024; Goldman et al., 2025; Hong et al., 2025) of an LLM cannot be understood independently of the *specific task*. That is, more “complex” problems will exhibit degradation at even *shorter* lengths than simpler ones. Because of this, we must characterize tasks in terms of how their complexity *scales with prompt length*.

For example, needle-in-a-haystack (NIAH) problems generally keep ‘needles’ constant as prompt length is scaled. As a result, frontier models can now reliably solve these tasks in RULER (Hsieh et al., 2024) in the 1M+ token settings but struggle at far shorter lengths on OOLONG (Bertsch et al., 2025), a task where the answer depends explicitly on almost every line in the prompt.²

3.1. Tasks

We design our evaluation around tasks where we can vary the lengths of the prompts, so we can consider problems whose difficulties scale differently with context length.

S-NIAH. Following the single needle-in-the-haystack task in RULER (Hsieh et al., 2024), we consider a set of 50 single tasks that require finding a specific phrase or number in a large set of unrelated text. Here, the information being sought scales as $O(1)$ with respect to input length.

BrowseComp-Plus (1K documents) (Chen et al., 2025). A multi-hop question-answering benchmark for DeepResearch (OpenAI, 2025a) questions that requires reasoning over multiple different documents. The benchmark provides a verified offline corpus that is guaranteed to contain gold, evidence, and hard negative documents for each question. Following Sun et al. (2025), we use 150 randomly sampled instances as our evaluation set; we provide 1000 randomly chosen documents as input, in which the gold and evidence documents are guaranteed to exist. We report the percentage of correct answers. The answer to each task requires piecing together information from several documents, making this harder than S-NIAH despite also requiring a constant number of documents.

OOLONG (Bertsch et al., 2025). A long reasoning benchmark that requires transforming chunks of the input semantically, then aggregating these chunks to form a final answer. We report scoring based on the original paper, which scores numerical answers as $\text{score}(\hat{y}) = 0.75^{|y-\hat{y}|}$ and other answers as exact match. We focus specifically on the `trec_coarse` split, a set of 50 tasks over a dataset of

questions with semantic labels. Each task requires using nearly all entries of the dataset, and therefore scales linearly in processing complexity relative to the input length.

OOLONG-Pairs. We modify the `trec_coarse` split of OOLONG to include 20 new queries that specifically require aggregating *pairs* of chunks to construct the final answer. We report F1 scores over the answer. Each task requires using nearly all *pairs* of entries of the dataset, and therefore requires processing quadratically-many items relative to the input length. In Appendix D.1, we provide all queries in this benchmark.

LongBench-v2 CodeQA (Bai et al., 2025). A multi-choice code repository understanding split from LongBench-v2 that is challenging for modern frontier models. We report the score as the percentage of correct answers. Each instance requires reasoning over a fixed number of files in a codebase to find the right answer.

3.2. Methods and Baselines

We compare RLMs against commonly used task-agnostic inference methods, using two modern LMs, GPT-5 with medium reasoning (Singh et al., 2025) and default sampling parameters, and Qwen3-Coder-480B-A35B (Yang et al., 2025) using the sampling parameters described in Qwen Team (2025b). For Qwen3-Coder-480B-A35B, we compute costs based on the compute provider Fireworks (Fireworks AI, 2025). In addition to evaluating the base model on all tasks, we also evaluate the following methods and baselines:

CodeAct (+ BM25). We compare directly to a CodeAct (Wang et al., 2024) agent that can execute code inside of a ReAct (Yao et al., 2023) loop. Unlike an RLM, CodeAct does not offload the user prompt to the code environment, and instead provides it directly to the LM. Furthermore, following Jimenez et al. (2024); Chen et al. (2025), we equip this agent with a BM25 (Robertson & Zaragoza, 2009) retriever that indexes the input context for tasks where a retriever is appropriate.

CodeAct with sub-calls. To specifically ablate offloading the context as a variable in the REPL, we evaluate a CodeAct (Wang et al., 2024) baseline with the ability to invoke sub-LM calls. Compared to RLMs, this method loads the context directly into the model.

Summary agent. Following Sun et al. (2025); Wu et al. (2025); Yu et al. (2025), we consider an iterative agent that compacts the context as it is filled. For example, given a corpus of documents, it will iteratively accumulate the documents and summarize when full. In cases where a single document exceeds the model window, the agent will chunk it to fit within the model context window and invoke the same strategy over these chunks. For the GPT-5 experiments, due to the extremely high cost of applying this strategy to

²This helps explain the patterns seen in Figure 1 earlier: GPT-5 scales effectively on the S-NIAH task, where the needle size is constant despite longer prompts, but shows faster degradation at increasingly *shorter* context lengths on the *linear*-complexity OOLONG and the *quadratic*-complexity OOLONG-Pairs.

Table 1. Performance comparison of different methods across long-context benchmarks of varying complexity. In gray is the average API cost \pm the standard deviation of each method on each task. * indicates runs where a method (sometimes) ran into input context limits. Provider costs were computed under OpenAI for GPT-5 and Fireworks for other models. Non-zero scores are rounded to at least 0.1.

Model	CodeQA	BrowseComp+ (1K)	OOLONG	OOLONG-Pairs
Task Length N (tokens)	23K-4.2M	6M-11M	131K	32K
GPT-5 (with RLM sub-calls to GPT-5-mini)				
Base Model	24.0* (\$0.13 \pm \$0.07)	0.0* (N/A) \pm (N/A)	44.0 (\$0.14 \pm \$0.02)	0.1 (\$0.16 \pm \$0.10)
CodeAct (+ BM25)	22.0* (\$0.06 \pm \$0.08)	51.0 (\$0.71 \pm \$1.20)	38.0 (\$0.61 \pm \$1.06)	24.7 (\$0.75 \pm \$0.43)
CodeAct (+ sub-calls)	24.0* (\$0.06 \pm \$0.08)	0.0* (N/A) \pm (N/A)	40.0 (\$0.85 \pm \$1.27)	28.4 (\$1.11 \pm \$0.62)
Summary agent	58.0 (\$1.31 \pm \$1.46)	70.5 (\$0.57 \pm \$0.10)	46.0 (\$0.13 \pm \$0.01)	0.1 (\$0.13 \pm \$0.09)
RLM	62.0 (\$0.11 \pm \$0.10)	91.3 (\$0.99 \pm \$1.22)	56.5 (\$0.43 \pm \$0.85)	58.0 (\$0.33 \pm \$0.20)
RLM (no sub-calls)	58.0 (\$0.18 \pm \$0.56)	88.0 (\$0.44 \pm \$0.90)	36.0 (\$0.37 \pm \$0.42)	43.9 (\$0.69 \pm \$1.16)
Qwen3-Coder-480B-A35B				
Base Model	20.0* (\$0.13 \pm \$0.08)	0.0* (N/A) \pm (N/A)	36.0 (\$0.06 \pm \$0.00)	0.1 (\$0.05 \pm \$0.01)
CodeAct (+ BM25)	24.0* (\$0.17 \pm \$0.08)	12.7 (\$0.39 \pm \$0.50)	38.0 (\$1.51 \pm \$1.09)	0.3 (\$1.54 \pm \$0.35)
CodeAct (+ sub-calls)	26.0* (\$0.28 \pm \$0.30)	0.0* (N/A) \pm (N/A)	32.0 (\$1.83 \pm \$1.14)	0.1 (\$1.49 \pm \$0.46)
Summary agent	50.0 (\$1.26 \pm \$1.50)	38.0 (\$8.98 \pm \$2.12)	44.1 (\$0.15 \pm \$0.01)	0.31 (\$0.05 \pm \$0.00)
RLM	56.0 (\$0.92 \pm \$1.23)	44.7 (\$0.84 \pm \$0.63)	48.0 (\$0.61 \pm \$0.49)	23.1 (\$1.02 \pm \$0.52)
RLM (no sub-calls)	66.0 (\$0.18 \pm \$0.58)	46.0 (\$0.82 \pm \$0.69)	43.5 (\$0.32 \pm \$0.13)	17.3 (\$1.77 \pm \$1.23)
Qwen3-8B				
Base Model	4.0* (\$0.01 \pm \$0.00)	0.0* (N/A) \pm (N/A)	0.0* (N/A) \pm (N/A)	0.1 (\$0.01 \pm \$0.00)
RLM	26.0 (\$0.04 \pm \$0.13)	2.0 (\$0.03 \pm \$0.06)	24.0 (\$0.19 \pm \$0.26)	4.3 (\$0.05 \pm \$0.05)
RLM (fine-tuned)	32.0 (\$0.02 \pm \$0.02)	14.0 (\$0.01 \pm \$0.03)	32.0 (\$0.04 \pm \$0.09)	5.2 (\$0.02 \pm \$0.02)

millions of tokens, we use GPT-5-nano for compaction and GPT-5 to provide the final answer.

RLM with REPL. We implement an RLM with a Python REPL environment, which loads a module for querying a sub-LM and uses a system prompt presented in Appendix C. For the GPT-5 experiments, we use GPT-5-mini for the recursive LMs and GPT-5 for the root LM, as we found this choice to strike a good balance between the capabilities of RLMs and the cost of the recursive calls. We notate a RLM using a model as RLM(model), e.g. RLM(GPT-5).

RLM with REPL, no sub-calls. We provide an ablation of our method, in which the prompt is loaded in a REPL environment without the ability to invoke sub-LM calls.

Finetuning. To create **RLM-Qwen3-8B**, we finetune Qwen3-8B on 1,000 filtered trajectories of Qwen3-Coder-480B-A35B as an RLM with Qwen3-8B sub-calls on Long-BenchPro (Chen et al., 2026) tasks. We use sampling parameters described in Qwen Team (2025a), and evaluate the fine-tuned RLM-Qwen3-8B as an RLM on our long context tasks. The key insight for training is that being an effective

sub-call model is roughly similar to being a general purpose reasoning model, so we can make the training much more tractable (and seemingly short-horizon) at small scale by focusing on improving the root model’s ability to manipulate the REPL and to launch recursive calls. We provide more training details in Appendix A.

4. Results and Discussion

Table 1 reports our main results. We additionally explore how vanilla frontier model performance and RLM performance degrades as input contexts grow in Figure 1.

Observation 1: RLMs can scale to the 10M+ token regime and can outperform base LMs and existing task-agnostic agent scaffolds on long context tasks. Across all tasks, RLMs demonstrate strong performance on prompts well beyond the effective context window of a frontier LM, outperforming base models and common long-context scaffolds by up to $2\times$ the performance while maintaining comparable or cheaper average token costs. Notably, RLMs scale well beyond the base models’ context window. For

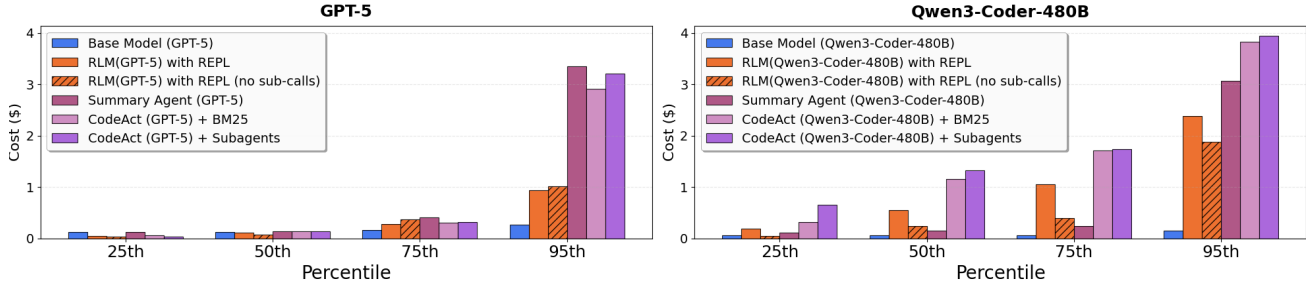


Figure 3. Cost of RLM and baselines described in §3.2 plotted at the 25th, 50th, 75th, and 95th percentile of total API cost. We observe comparable or even lower costs for RLMs at the 50th percentile, but sharp increases at the tail end due to potentially long RLM trajectories.

instance, on BrowseComp-Plus (1K), a linearly extrapolated cost for GPT-5-mini ingesting 6-11M input tokens is \$1.50 – \$2.75, while RLM(GPT-5) has an average cost of \$0.99 and outperforms both the summarization and retrieval baselines by over 29%.

Furthermore, on tasks where processing costs scale with the input context, RLMs make significant improvements over the base model, even on tasks within the model’s context window. On OOLONG, the RLM with GPT-5 and Qwen3-Coder outperform the base model by 28.4% and 33.3% respectively. On OOLONG-Pairs, both GPT-5 and Qwen3-Coder make little progress with F1 scores of <0.1%, while the RLM using these models achieve F1 scores of 58.0% and 23.1% respectively, highlighting the emergent capability of RLMs to handle extremely information-dense tasks.

Observation 2: The REPL is necessary for handling long inputs, while the recursive sub-calling of RLMs provides strong benefits on information-dense inputs. A key characteristic of RLMs is offloading the context as a variable in an environment \mathcal{E} that the model can interact with. Even without sub-calling capabilities, our ablation of the RLM is able to scale beyond the context limit of the model and outperform other task-agnostic baselines on most long context settings. On the CodeQA and BrowseComp+ tasks with Qwen3-Coder, this ablation is able to outperform the RLM by 17.9% and 3% respectively.

On information-dense tasks like OOLONG or OOLONG-Pairs, we observed several cases where recursive LM sub-calling is necessary. In §4.1, we see RLM(Qwen3-Coder) perform the necessary semantic transformation line-by-line through recursive sub-calls, while the ablation without sub-calls is forced to use keyword heuristics to solve these tasks. Across all information-dense tasks, RLMs outperform the ablation without sub-calling by 10%-59%.

Observation 3: LM performance degrades as a function of input length and problem complexity, while RLM performance scales better. The benchmarks S-NIAH, OOLONG, and OOLONG-Pairs contain a fixed number of tasks over contexts with lengths ranging from 2^{13} to 2^{18} . Each

benchmark can be loosely categorized by different processing complexity of the input context with respect to length (roughly constant, linear, and quadratic respectively). In Figure 1, we directly compare an RLM using GPT-5 to base GPT-5 on each task. We find that GPT-5 performance degrades significantly faster for more complex tasks, while RLM performance degrades at a much slower rate, which aligns with the findings of Goldman et al. (2025). For context lengths beyond 2^{14} , the RLM consistently outperforms GPT-5.

Furthermore, RLM costs scale proportionally to the complexity of the task, while still remaining in the same order of magnitude of cost as GPT-5 (see Figure 11 in Appendix F). In §4.1, we explore the choices that the RLM makes that cause these differences in cost. Lastly, in this setting, we also observe that the base LM outperforms RLM in the small input context regime. By construction, a RLM has strictly more representation capacity than an LM. In practice, however, we observe that RLM performance is slightly worse on smaller input lengths, suggesting a tradeoff point between when to use a base LM and when to use an RLM.

Observation 4: The inference cost of RLMs remains comparable to a base LM call but has high variance due to differences in trajectory lengths. RLMs iteratively interact with their context until they find a suitable answer, leading to large differences in iteration length depending on task complexity. In Figure 3, we plot the quartile costs for each method across all experiments in Table 1 excluding BrowseComp-Plus (1K), as the base models cannot fit any of these tasks in context. For GPT-5, the median RLM run is cheaper than the median base model run, but many outlier RLM runs are significantly more expensive than any base model query. However, compared to the summarization agent which ingests the entire input context, RLMs are up to $3\times$ cheaper while maintaining stronger performance across all tasks because the RLM is able to selectively view context.

We additionally report runtime numbers of each method in Figures 7, 8 in Appendix F, but we note several important caveats. Unlike API costs, these numbers are heavily dependent on implementation details such as the machine used,

API request latency, and the asynchrony of LM calls. In our implementation of the baselines and RLMs, all LM calls are blocking / sequential. Nevertheless, similar to costs, we observe a wide range of runtimes, especially for RLMs.

Observation 5: RLMs are a model-agnostic inference strategy, but different models exhibit different overall decisions on context management and sub-calling. While GPT-5 and Qwen3-Coder-480B both exhibit strong performance as RLMs relative to their base model and other baselines, they also exhibit different performance and behavior across all tasks. On BrowseComp-Plus (1k) in particular, RLM(GPT-5) nearly solves all tasks while RLM(Qwen3-Coder) struggles to solve half.

We note that the RLM system prompt is fixed for each model across all experiments and is not tuned for any particular benchmark. Between GPT-5 and Qwen3-Coder, the only difference in the prompt is an extra line in the RLM(Qwen3-Coder) prompt warning against using too many sub-calls (see Appendix C). We provide an explicit example of this difference in example E.3, where RLM(Qwen3-Coder) launches a sub-call per line in OOLONG while GPT-5 is conservative about sub-querying LMs.

Observation 6: Training RLMs on one domain can improve general downstream RLM performance. Certain behavior in RLM trajectories are common among different domains, such as probing the input and recursively sub-calling on shorter contexts. In Table 1, we find that **RLM-Qwen3-8B**, a Qwen3-8B model that we fine-tuned on RLM(Qwen3-Coder-480B-A35B) trajectories on a small, *unrelated* set of tasks (LongBenchPro; Chen et al. 2026) considerably outperforms the base Qwen3-8B as an RLM by 28.3% on average. Furthermore, its inference costs are much lower due to better decision making and fewer mistakes as an RLM.

4.1. Emergent Patterns in RLM Trajectories

Even without explicit training, RLMs exhibit interesting context and problem decomposition behavior. We select several examples of snippets from RLM trajectories to understand how they solve long context problems and where they can improve. We discuss particular examples of interesting behavior here, with additional examples in Appendix E.

Chunking and recursively sub-calling LMs. RLMs defer essentially unbounded-length reasoning chains to sub-LM calls. The choice of decomposition can greatly affect task performance, especially for information-dense problems. In our experiments, we did not observe complicated partitioning strategies beyond uniform chunking or keyword searches. In Figure 4b, RLM(Qwen3-Coder) chunks by newline in a 1000+ line context from OOLONG.

Filtering input information using code execution based

on model priors. A key intuition for why the RLM abstraction can maintain strong performance on huge inputs without exploding costs is the LM’s ability to filter input context without explicitly seeing it. Furthermore, model priors enable the RLM to narrow the search space and process fewer input tokens. As an example, in Figure 4a, we observed RLM(GPT-5) using `regex` queries to search for chunks containing keywords in the original prompt (e.g. “festival”) and phrases it has a prior about (e.g. “La Union”).

Passing recursive LM outputs through variables for long output tasks. RLMs are able to produce essentially unbounded tokens well beyond the limit of the base LM by returning variables in the REPL as output. Through the REPL, the RLM can iteratively construct these variables as a mixture of programmatic and sub-(R)LM output calls. We observed this strategy used heavily in OOLONG-Pairs trajectories, where the RLM stored the output of sub-LM calls over the input in variables and stitched them together to form a final answer (see Figure 4c).

5. Related Works

Long-Context LM Systems. There have primarily been two orthogonal directions for long-context management in language model systems: 1) directly changing the architecture of and retraining the base LM to handle longer contexts (Press et al., 2022; Gu et al., 2022; Munkhdalai et al., 2024), and 2) building a scaffold around the LM that implicitly handles the context – RLMs focus on the latter. One popular class of such strategies is *lossy* context management, which uses summarization or truncation to compress the input context at the cost of potentially losing fine-grained information. For example, MemWalker (Chen et al., 2023) constructs a tree-like data structure of the input that the LM can navigate when answering long context questions. ReSum (Wu et al., 2025) is another work that adds a summarization tool to periodically compress the context of a multi-turn agent. Another class of strategies implement an explicit memory hierarchy in the agent scaffold (Packer et al., 2024; Chhikara et al., 2025; Zhang et al., 2025). RLMs differ from these works in that all context window management is implicitly handled by the LM itself.

Task Decomposition through sub-LM calls. Many LM-based agents (Guo et al., 2024; Anthropic, 2025) use multiple, well-placed LM calls to solve a problem; however, many of these calls are placed based on human-engineered workflows. Several methods like ViperGPT (Surís et al., 2023), THREAD (Schroeder et al., 2025), DisCIPL (Grand et al., 2025), ReDel (Zhu et al., 2024), Context Folding (Sun et al., 2025), and AgentFold (Ye et al., 2025) have explored deferring the choice of sub-LM calls to the LM. These techniques emphasize *task* decomposition through recursive LM calls, but are unable to handle long context inputs beyond



Figure 4. RLMs have common patterns in their trajectories when solving tasks. (a) We frequently observed RLMs filtering and interacting with their context through `regex` code. (b) We found that RLMs can effectively decompose their context through recursive sub-calls (c) On long-output tasks, RLMs are able to solve sub-problems using recursive sub-LM calls and stitch their outputs to form a final output.

the length of the base LM. RLMs, on the other hand, are enabled by an extremely simple intuition (i.e., placing the prompt in the external environment) to *symbolically* manipulate arbitrarily long strings and to iteratively refine their recursion via execution feedback from the persistent REPL.

6. Limitations and Future Work

While RLMs show strong performance on tasks beyond the context window limitations of existing LMs at reasonable inference costs, evaluations for more difficult and natural long-context processing tasks and the best mechanisms for implementing RLMs both remain highly under-explored. We focused on synchronous sub-calls inside of a Python REPL environment, but we note that alternative strategies involving asynchronous sub-calls and sandboxed REPLs can potentially significantly reduce the runtime and inference cost of RLMs. Furthermore, we chose to use a max recursion depth of one (i.e. sub-calls are LMs); while we found strong performance on existing long-context benchmarks, we believe that future work should investigate deeper levels of recursion or even new hybrids between symbolic recursion and neural attention. We include additional limitations and negative results in Appendix B.

Lastly, we focused our experiments on evaluating RLMs using *existing* frontier models, but show initial evidence on a Qwen3-8B model that explicitly training a model to be used

as a RLM provides very rapid performance improvements, even outside the training domain. We hypothesize that RLM trajectories can be viewed as a form of reasoning (OpenAI et al., 2024; DeepSeek-AI et al., 2025), which can be trained by bootstrapping existing models (Zelikman et al., 2022; 2024). We hope that training native RLMs can be treated as a new axis of scale to improve LM performance on general and long-horizon tasks.

7. Conclusion

We introduced Recursive Language Models (RLMs), a general inference framework for language models that offloads the input context and enables language models to recursively sub-query language models before providing an output. We explored an instantiation of this framework that offloads the context into a Python REPL environment as a variable in memory, enabling the LM to reason over its context in code and recursive LM calls, rather than purely in token space. Our results across multiple settings and models demonstrated that RLMs are an effective task-agnostic paradigm for both long-context problems and general reasoning. Building on our small fine-tuning experiments, we are excited to see future work that explicitly trains models to reason as RLMs, which could result in another axis of scale for the next generation of language model systems.

8. Impact Statement

This paper explores a strategy for enabling language models to solve long context problems and scaling future language model systems. The goal is to advance research on systems that can help us solve complex problems. While there are potential societal consequences of this work, we believe they are not specific to this paper and do not need to be highlighted here.

Acknowledgments

This research is partially supported by the Laude Institute, Prime Intellect, and Modal Labs. We thank Noah Ziemis, Jacob Li, James Moore, and the MIT OASYS and MIT DSG labs for insightful discussions throughout this project. We also thank Jack Cook, Matej Sirovatka, Ofir Press, Sebastian Müller, Simon Guo, and Zed Li for helpful feedback.

References

- Anthropic. Claude code: Subagents — modular ai workflows with isolated agent contexts, 2025. URL <https://docs.anthropic.com/en/docs/claude-code/sub-agents>.
- Bai, Y., Tu, S., Zhang, J., Peng, H., Wang, X., Lv, X., Cao, S., Xu, J., Hou, L., Dong, Y., Tang, J., and Li, J. Longbench v2: Towards deeper understanding and reasoning on realistic long-context multitasks, 2025. URL <https://arxiv.org/abs/2412.15204>.
- Bertsch, A., Pratapa, A., Mitamura, T., Neubig, G., and Gormley, M. R. Oolong: Evaluating long context reasoning and aggregation capabilities, 2025. URL <https://arxiv.org/abs/2511.02817>.
- Chang, Y., Lo, K., Goyal, T., and Iyyer, M. Boookscore: A systematic exploration of book-length summarization in the era of LLMs. In *The Twelfth International Conference on Learning Representations*, 2024. URL <https://arxiv.org/pdf/2310.00785.pdf>.
- Chen, H., Pasunuru, R., Weston, J., and Celikyilmaz, A. Walking down the memory maze: Beyond context limit through interactive reading, 2023. URL <https://arxiv.org/abs/2310.05029>.
- Chen, Z., Ma, X., Zhuang, S., Nie, P., Zou, K., Liu, A., Green, J., Patel, K., Meng, R., Su, M., Sharifmoghammad, S., Li, Y., Hong, H., Shi, X., Liu, X., Thakur, N., Zhang, C., Gao, L., Chen, W., and Lin, J. Browsecomp-plus: A more fair and transparent evaluation benchmark of deep-research agent, 2025. URL <https://arxiv.org/abs/2508.06600>.
- Chen, Z., Wu, X., Jia, J., Gao, C., Fu, Q., Zhang, D., and Hu, S. Longbench pro: A more realistic and comprehensive bilingual long-context evaluation benchmark, 2026. URL <https://arxiv.org/abs/2601.02872>.
- Chhikara, P., Khant, D., Aryan, S., Singh, T., and Yadav, D. Mem0: Building production-ready ai agents with scalable long-term memory, 2025. URL <https://arxiv.org/abs/2504.19413>.
- DeepSeek-AI, Guo, D., Yang, D., Zhang, H., Song, J., Zhang, R., Xu, R., Zhu, Q., Ma, S., Wang, P., Bi, X., Zhang, X., Yu, X., Wu, Y., Wu, Z. F., Gou, Z., Shao, Z., Li, Z., Gao, Z., Liu, A., Xue, B., Wang, B., Wu, B., Feng, B., Lu, C., Zhao, C., Deng, C., Zhang, C., Ruan, C., Dai, D., Chen, D., Ji, D., Li, E., Lin, F., Dai, F., Luo, F., Hao, G., Chen, G., Li, G., Zhang, H., Bao, H., Xu, H., Wang, H., Ding, H., Xin, H., Gao, H., Qu, H., Li, H., Guo, J., Li, J., Wang, J., Chen, J., Yuan, J., Qiu, J., Li, J., Cai, J. L., Ni, J., Liang, J., Chen, J., Dong, K., Hu, K., Gao, K., Guan, K., Huang, K., Yu, K., Wang, L., Zhang, L., Zhao, L., Wang, L., Zhang, L., Xu, L., Xia, L., Zhang, M., Zhang, M., Tang, M., Li, M., Wang, M., Li, M., Tian, N., Huang, P., Zhang, P., Wang, Q., Chen, Q., Du, Q., Ge, R., Zhang, R., Pan, R., Wang, R., Chen, R. J., Jin, R. L., Chen, R., Lu, S., Zhou, S., Chen, S., Ye, S., Wang, S., Yu, S., Zhou, S., Pan, S., Li, S. S., Zhou, S., Wu, S., Ye, S., Yun, T., Pei, T., Sun, T., Wang, T., Zeng, W., Zhao, W., Liu, W., Liang, W., Gao, W., Yu, W., Zhang, W., Xiao, W. L., An, W., Liu, X., Wang, X., Chen, X., Nie, X., Cheng, X., Liu, X., Xie, X., Liu, X., Yang, X., Li, X., Su, X., Lin, X., Li, X. Q., Jin, X., Shen, X., Chen, X., Sun, X., Wang, X., Song, X., Zhou, X., Wang, X., Shan, X., Li, Y. K., Wang, Y. Q., Wei, Y. X., Zhang, Y., Xu, Y., Li, Y., Zhao, Y., Sun, Y., Wang, Y., Yu, Y., Zhang, Y., Shi, Y., Xiong, Y., He, Y., Piao, Y., Wang, Y., Tan, Y., Ma, Y., Liu, Y., Guo, Y., Ou, Y., Wang, Y., Gong, Y., Zou, Y., He, Y., Xiong, Y., Luo, Y., You, Y., Liu, Y., Zhou, Y., Zhu, Y. X., Xu, Y., Huang, Y., Li, Y., Zheng, Y., Zhu, Y., Ma, Y., Tang, Y., Zha, Y., Yan, Y., Ren, Z. Z., Ren, Z., Sha, Z., Fu, Z., Xu, Z., Xie, Z., Zhang, Z., Hao, Z., Ma, Z., Yan, Z., Wu, Z., Gu, Z., Zhu, Z., Liu, Z., Li, Z., Xie, Z., Song, Z., Pan, Z., Huang, Z., Xu, Z., Zhang, Z., and Zhang, Z. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning, 2025. URL <https://arxiv.org/abs/2501.12948>.
- Fireworks AI. Qwen3 coder 480b a35b instruct. <https://fireworks.ai/models/fireworks/qwen3-coder-480b-a35b-instruct>, 2025.
- Goldman, O., Jacovi, A., Slobodkin, A., Maimon, A., Dagan, I., and Tsarfaty, R. Is it really long context if all you need is retrieval? towards genuinely difficult long context nlp, 2025. URL <https://arxiv.org/abs/2407.00402>.

- Grand, G., Tenenbaum, J. B., Mansinghka, V. K., Lew, A. K., and Andreas, J. Self-steering language models. *arXiv preprint arXiv:2504.07081*, 2025.
- Gu, A., Goel, K., and Ré, C. Efficiently modeling long sequences with structured state spaces, 2022. URL <https://arxiv.org/abs/2111.00396>.
- Guo, T., Chen, X., Wang, Y., Chang, R., Pei, S., Chawla, N. V., Wiest, O., and Zhang, X. Large language model based multi-agents: A survey of progress and challenges, 2024. URL <https://arxiv.org/abs/2402.01680>.
- Hong, K., Troynikov, A., and Huber, J. Context rot: How context degradation affects llm performance, 2025. URL <https://research.trychroma.com/context-rot>.
- Hsieh, C.-P., Sun, S., Krizan, S., Acharya, S., Rekesh, D., Jia, F., Zhang, Y., and Ginsburg, B. Ruler: What’s the real context size of your long-context language models?, 2024. URL <https://arxiv.org/abs/2404.06654>.
- Intellect, P. Prime rl library, 2025. URL <https://github.com/PrimeIntellect-ai/prime-rl>.
- Jimenez, C. E., Yang, J., Wettig, A., Yao, S., Pei, K., Press, O., and Narasimhan, K. Swe-bench: Can language models resolve real-world github issues?, 2024. URL <https://arxiv.org/abs/2310.06770>.
- Khattab, O., Potts, C., and Zaharia, M. Baleen: Robust multi-hop reasoning at scale via condensed retrieval. *Advances in Neural Information Processing Systems*, 34: 27670–27682, 2021.
- Merrill, W. and Sabharwal, A. The expressive power of transformers with chain of thought. In *The Twelfth International Conference on Learning Representations*, 2024.
- Munkhdalai, T., Faruqui, M., and Gopal, S. Leave no context behind: Efficient infinite context transformers with infini-attention, 2024. URL <https://arxiv.org/abs/2404.07143>.
- OpenAI. Deep research, 2025a. URL <https://openai.com/index/introducing-deep-research/>. AI-powered research assistant tool.
- OpenAI. Codex cli: A lightweight coding agent for your terminal, 2025b. URL <https://developers.openai.com/codex/cli/>.
- OpenAI, Jaech, A., Kalai, A., Lerer, A., Richardson, A., El-Kishky, A., Low, A., Helyar, A., Madry, A., Beutel, A., Carney, A., Iftimie, A., Karpenko, A., Passos, A. T., Neitz, A., Prokofiev, A., Wei, A., Tam, A., Bennett, A., Kumar, A., Saraiva, A., Vallone, A., Duberstein, A., Kondrich, A., Mishchenko, A., Applebaum, A., Jiang, A., Nair, A., Zoph, B., Ghorbani, B., Rossen, B., Sokolowsky, B., Barak, B., McGrew, B., Minaiev, B., Hao, B., Baker, B., Houghton, B., McKinzie, B., Eastman, B., Lugaresi, C., Bassin, C., Hudson, C., Li, C. M., de Bourcy, C., Voss, C., Shen, C., Zhang, C., Koch, C., Orsinger, C., Hesse, C., Fischer, C., Chan, C., Roberts, D., Kappler, D., Levy, D., Selsam, D., Dohan, D., Farhi, D., Mely, D., Robinson, D., Tsipras, D., Li, D., Oprica, D., Freeman, E., Zhang, E., Wong, E., Proehl, E., Cheung, E., Mitchell, E., Wallace, E., Ritter, E., Mays, E., Wang, F., Such, F. P., Raso, F., Leoni, F., Tsimpouras, F., Song, F., von Lohmann, F., Sulit, F., Salmon, G., Parascandolo, G., Chabot, G., Zhao, G., Brockman, G., Leclerc, G., Salman, H., Bao, H., Sheng, H., Andrin, H., Bagherinezhad, H., Ren, H., Lightman, H., Chung, H. W., Kivlichan, I., O’Connell, I., Osband, I., Gilaberte, I. C., Akkaya, I., Kostrikov, I., Sutskever, I., Kofman, I., Pachocki, J., Lennon, J., Wei, J., Harb, J., Twore, J., Feng, J., Yu, J., Weng, J., Tang, J., Yu, J., Candela, J. Q., Palermo, J., Parish, J., Heidecke, J., Hallman, J., Rizzo, J., Gordon, J., Uesato, J., Ward, J., Huizinga, J., Wang, J., Chen, K., Xiao, K., Singhal, K., Nguyen, K., Cobbe, K., Shi, K., Wood, K., Rimbach, K., Gu-Lemberg, K., Liu, K., Lu, K., Stone, K., Yu, K., Ahmad, L., Yang, L., Liu, L., Maksin, L., Ho, L., Fedus, L., Weng, L., Li, L., McCallum, L., Held, L., Kuhn, L., Kondraciuk, L., Kaiser, L., Metz, L., Boyd, M., Trebacz, M., Joglekar, M., Chen, M., Tintor, M., Meyer, M., Jones, M., Kaufer, M., Schwarzer, M., Shah, M., Yatbaz, M., Guan, M. Y., Xu, M., Yan, M., Glaese, M., Chen, M., Lampe, M., Malek, M., Wang, M., Fradin, M., McClay, M., Pavlov, M., Wang, M., Wang, M., Murati, M., Bavarian, M., Rohaninejad, M., McAleese, N., Chowdhury, N., Chowdhury, N., Ryder, N., Tezak, N., Brown, N., Nachum, O., Boiko, O., Murk, O., Watkins, O., Chao, P., Ashbourne, P., Izmailov, P., Zhokhov, P., Dias, R., Arora, R., Lin, R., Lopes, R. G., Gaon, R., Miyara, R., Leike, R., Hwang, R., Garg, R., Brown, R., James, R., Shu, R., Cheu, R., Greene, R., Jain, S., Altman, S., Toizer, S., Toyer, S., Miserendino, S., Agarwal, S., Hernandez, S., Baker, S., McKinney, S., Yan, S., Zhao, S., Hu, S., Santurkar, S., Chaudhuri, S. R., Zhang, S., Fu, S., Papay, S., Lin, S., Balaji, S., Sanjeev, S., Sidor, S., Broda, T., Clark, A., Wang, T., Gordon, T., Sanders, T., Patwardhan, T., Sottiaux, T., Degry, T., Dimson, T., Zheng, T., Garipov, T., Stasi, T., Bansal, T., Creech, T., Peterson, T., Eloundou, T., Qi, V., Kosaraju, V., Monaco, V., Pong, V., Fomenko, V., Zheng, W., Zhou, W., McCabe, W., Zaremba, W., Dubois, Y., Lu, Y., Chen, Y., Cha, Y., Bai, Y., He, Y., Zhang, Y., Wang, Y., Shao, Z., and Li, Z. Openai o1 system card, 2024. URL <https://arxiv.org/abs/2412.16720>.
- Packer, C., Wooders, S., Lin, K., Fang, V., Patil, S. G.,

- Stoica, I., and Gonzalez, J. E. Memgpt: Towards llms as operating systems, 2024. URL <https://arxiv.org/abs/2310.08560>.
- Press, O., Smith, N. A., and Lewis, M. Train short, test long: Attention with linear biases enables input length extrapolation, 2022. URL <https://arxiv.org/abs/2108.12409>.
- Qwen Team. Qwen3-8b. <https://huggingface.co/Qwen/Qwen3-8B>, 2025a.
- Qwen Team. Qwen3-coder-480b-a35b-instruct. <https://huggingface.co/Qwen/Qwen3-Coder-480B-A35B-Instruct>, 2025b.
- Redmon, J. and Farhadi, A. Yolov3: An incremental improvement, 2018. URL <https://arxiv.org/abs/1804.02767>.
- Robertson, S. and Zaragoza, H. The probabilistic relevance framework: Bm25 and beyond. *Found. Trends Inf. Retr.*, 3(4):333–389, April 2009. ISSN 1554-0669. doi: 10.1561/15000000019. URL <https://doi.org/10.1561/15000000019>.
- Schroeder, P., Morgan, N., Luo, H., and Glass, J. Thread: Thinking deeper with recursive spawning, 2025. URL <https://arxiv.org/abs/2405.17402>.
- Sentient AI. Roma: The backbone for open-source meta-agents, November 2025. URL <https://blog.sentient.xyz/posts/recursive-open-meta-agent>. Accessed: 2025-12-20.
- Singh, A., Fry, A., Perelman, A., Tart, A., Ganesh, A., El-Kishky, A., McLaughlin, A., Low, A., Ostrow, A., Ananthram, A., Nathan, A., Luo, A., Helyar, A., Madry, A., Efremov, A., Spyra, A., Baker-Whitcomb, A., Beutel, A., Karpenko, A., Makelov, A., Neitz, A., Wei, A., Barr, A., Kirchmeyer, A., Ivanov, A., Christakis, A., Gillespie, A., Tam, A., Bennett, A., Wan, A., Huang, A., Sandjideh, A. M., Yang, A., Kumar, A., Saraiva, A., Vallone, A., Gheorghe, A., Garcia, A. G., Braunstein, A., Liu, A., Schmidt, A., Mereskin, A., Mishchenko, A., Applebaum, A., Rogerson, A., Rajan, A., Wei, A., Kotha, A., Srivastava, A., Agrawal, A., Vijayvergiya, A., Tyra, A., Nair, A., Nayak, A., Eggers, B., Ji, B., Hoover, B., Chen, B., Chen, B., Barak, B., Minaiev, B., Hao, B., Baker, B., Lightcap, B., McKinzie, B., Wang, B., Quinn, B., Fioca, B., Hsu, B., Yang, B., Yu, B., Zhang, B., Brenner, B., Zetino, C. R., Raymond, C., Lugaresi, C., Paz, C., Hudson, C., Whitney, C., Li, C., Chen, C., Cole, C., Voss, C., Ding, C., Shen, C., Huang, C., Colby, C., Hallacy, C., Koch, C., Lu, C., Kaplan, C., Kim, C., Minott-Henriques, C., Frey, C., Yu, C., Czarnecki, C., Reid, C., Wei, C., Decareaux, C., Scheau, C., Zhang, C., Forbes, C., Tang, D., Goldberg, D., Roberts, D., Palmie, D., Kappler, D., Levine, D., Wright, D., Leo, D., Lin, D., Robinson, D., Grabb, D., Chen, D., Lim, D., Salama, D., Bhattacharjee, D., Tsipras, D., Li, D., Yu, D., Strouse, D., Williams, D., Hunn, D., Bayes, E., Arbus, E., Akyurek, E., Le, E. Y., Widmann, E., Yani, E., Proehl, E., Sert, E., Cheung, E., Schwartz, E., Han, E., Jiang, E., Mitchell, E., Sigler, E., Wallace, E., Ritter, E., Kavanaugh, E., Mays, E., Nikishin, E., Li, F., Such, F. P., de Avila Belbute Peres, F., Raso, F., Bekerman, F., Tsimpourlas, F., Chantzis, F., Song, F., Zhang, F., Raila, G., McGrath, G., Briggs, G., Yang, G., Parascandolo, G., Chabot, G., Kim, G., Zhao, G., Valiant, G., Leclerc, G., Salman, H., Wang, H., Sheng, H., Jiang, H., Wang, H., Jin, H., Sikchi, H., Schmidt, H., Aspegren, H., Chen, H., Qiu, H., Lightman, H., Covert, I., Kivlichan, I., Silber, I., Sohl, I., Hammoud, I., Clavera, I., Lan, I., Akkaya, I., Kostrikov, I., Kofman, I., Etinger, I., Singal, I., Hehir, J., Huh, J., Pan, J., Wilczynski, J., Pachocki, J., Lee, J., Quinn, J., Kiros, J., Kalra, J., Samaroo, J., Wang, J., Wolfe, J., Chen, J., Wang, J., Harb, J., Han, J., Wang, J., Zhao, J., Chen, J., Yang, J., Tworek, J., Chand, J., Landon, J., Liang, J., Lin, J., Liu, J., Wang, J., Tang, J., Yin, J., Jang, J., Morris, J., Flynn, J., Ferstad, J., Heidecke, J., Fishbein, J., Hallman, J., Grant, J., Chien, J., Gordon, J., Park, J., Liss, J., Kraaijeveld, J., Guay, J., Mo, J., Lawson, J., McGrath, J., Vendrow, J., Jiao, J., Lee, J., Steele, J., Wang, J., Mao, J., Chen, K., Hayashi, K., Xiao, K., Salahi, K., Wu, K., Sekhri, K., Sharma, K., Singhal, K., Li, K., Nguyen, K., Gu-Lemberg, K., King, K., Liu, K., Stone, K., Yu, K., Ying, K., Georgiev, K., Lim, K., Tirumala, K., Miller, K., Ahmad, L., Lv, L., Clare, L., Fauconnet, L., Itow, L., Yang, L., Romaniuk, L., Anise, L., Byron, L., Pathak, L., Maksin, L., Lo, L., Ho, L., Jing, L., Wu, L., Xiong, L., Mamitsuka, L., Yang, L., McCallum, L., Held, L., Bourgeois, L., Engstrom, L., Kuhn, L., Feuvrier, L., Zhang, L., Switzer, L., Kondraciuk, L., Kaiser, L., Joglekar, M., Singh, M., Shah, M., Stratta, M., Williams, M., Chen, M., Sun, M., Cayton, M., Li, M., Zhang, M., Aljube, M., Nichols, M., Haines, M., Schwarzer, M., Gupta, M., Shah, M., Huang, M., Dong, M., Wang, M., Glaese, M., Carroll, M., Lampe, M., Malek, M., Sharmman, M., Zhang, M., Wang, M., Pokrass, M., Florian, M., Pavlov, M., Wang, M., Chen, M., Wang, M., Feng, M., Bavarian, M., Lin, M., Abdool, M., Rohaninejad, M., Soto, N., Staudacher, N., LaFontaine, N., Marwell, N., Liu, N., Preston, N., Turley, N., Ansman, N., Blades, N., Pancha, N., Mikhaylin, N., Felix, N., Handa, N., Rai, N., Keskar, N., Brown, N., Nachum, O., Boiko, O., Murk, O., Watkins, O., Gleeson, O., Mishkin, P., Lesiewicz, P., Baltescu, P., Belov, P., Zhokhov, P., Pronin, P., Guo, P., Thacker, P., Liu, Q., Yuan, Q., Liu, Q., Dias, R., Puckett, R., Arora, R., Mullapudi, R. T., Gaon, R., Miyara, R., Song, R., Aggarwal, R., Marsan, R., Yemiru, R., Xiong,

- R., Kshirsagar, R., Nuttall, R., Tsiupa, R., Eldan, R., Wang, R., James, R., Ziv, R., Shu, R., Nigmatullin, R., Jain, S., Talaie, S., Altman, S., Arnesen, S., Toizer, S., Toyer, S., Miserendino, S., Agarwal, S., Yoo, S., Heon, S., Ethersmith, S., Grove, S., Taylor, S., Bubeck, S., Banerjee, S., Amdo, S., Zhao, S., Wu, S., Santurkar, S., Zhao, S., Chaudhuri, S. R., Krishnaswamy, S., Shuaiqi, Xia, Cheng, S., Anadkat, S., Fishman, S. P., Tobin, S., Fu, S., Jain, S., Mei, S., Egoian, S., Kim, S., Golden, S., Mah, S., Lin, S., Imm, S., Sharpe, S., Yadlowsky, S., Choudhry, S., Eum, S., Sanjeev, S., Khan, T., Stramer, T., Wang, T., Xin, T., Gogineni, T., Christianson, T., Sanders, T., Patwardhan, T., Degry, T., Shadwell, T., Fu, T., Gao, T., Garipov, T., Sriskandarajah, T., Sherbakov, T., Kaftan, T., Hiratsuka, T., Wang, T., Song, T., Zhao, T., Peterson, T., Kharitonov, V., Chernova, V., Kosaraju, V., Kuo, V., Pong, V., Verma, V., Petrov, V., Jiang, W., Zhang, W., Zhou, W., Xie, W., Zhan, W., McCabe, W., DePue, W., Ellsworth, W., Bain, W., Thompson, W., Chen, X., Qi, X., Xiang, X., Shi, X., Dubois, Y., Yu, Y., Khakbaz, Y., Wu, Y., Qian, Y., Lee, Y. T., Chen, Y., Zhang, Y., Xiong, Y., Tian, Y., Cha, Y., Bai, Y., Yang, Y., Yuan, Y., Li, Y., Zhang, Y., Yang, Y., Jin, Y., Jiang, Y., Wang, Y., Wang, Y., Liu, Y., Stubenvoll, Z., Dou, Z., Wu, Z., and Wang, Z. Openai gpt-5 system card, 2025. URL <https://arxiv.org/abs/2601.03267>.
- Smith, C. Openhands context condensation for more efficient ai agents, 2025. URL <https://openhands.dev/blog/openhands-context-condensation-for-more-efficient-ai-agents>.
- Sun, W., Lu, M., Ling, Z., Liu, K., Yao, X., Yang, Y., and Chen, J. Scaling long-horizon llm agent via context-folding, 2025. URL <https://arxiv.org/abs/2510.11967>.
- Surís, D., Menon, S., and Vondrick, C. Vipergpt: Visual inference via python execution for reasoning. *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, 2023.
- Wang, X., Chen, Y., Yuan, L., Zhang, Y., Li, Y., Peng, H., and Ji, H. Executable code actions elicit better llm agents, 2024. URL <https://arxiv.org/abs/2402.01030>.
- Wu, J., Ouyang, L., Ziegler, D. M., Stiennon, N., Lowe, R., Leike, J., and Christiano, P. Recursively summarizing books with human feedback, 2021. URL <https://arxiv.org/abs/2109.10862>.
- Wu, X., Li, K., Zhao, Y., Zhang, L., Ou, L., Yin, H., Zhang, Z., Yu, X., Zhang, D., Jiang, Y., Xie, P., Huang, F., Cheng, M., Wang, S., Cheng, H., and Zhou, J. Resum: Unlocking long-horizon search intelligence via context summarization, 2025. URL <https://arxiv.org/abs/2509.13313>.
- Yang, A., Li, A., Yang, B., Zhang, B., Hui, B., Zheng, B., Yu, B., Gao, C., Huang, C., Lv, C., Zheng, C., Liu, D., Zhou, F., Huang, F., Hu, F., Ge, H., Wei, H., Lin, H., Tang, J., Yang, J., Tu, J., Zhang, J., Yang, J., Yang, J., Zhou, J., Zhou, J., Lin, J., Dang, K., Bao, K., Yang, K., Yu, L., Deng, L., Li, M., Xue, M., Li, M., Zhang, P., Wang, P., Zhu, Q., Men, R., Gao, R., Liu, S., Luo, S., Li, T., Tang, T., Yin, W., Ren, X., Wang, X., Zhang, X., Ren, X., Fan, Y., Su, Y., Zhang, Y., Zhang, Y., Wan, Y., Liu, Y., Wang, Z., Cui, Z., Zhang, Z., Zhou, Z., and Qiu, Z. Qwen3 technical report, 2025. URL <https://arxiv.org/abs/2505.09388>.
- Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., and Cao, Y. React: Synergizing reasoning and acting in language models, 2023. URL <https://arxiv.org/abs/2210.03629>.
- Ye, R., Zhang, Z., Li, K., Yin, H., Tao, Z., Zhao, Y., Su, L., Zhang, L., Qiao, Z., Wang, X., Xie, P., Huang, F., Chen, S., Zhou, J., and Jiang, Y. Agentfold: Long-horizon web agents with proactive context management, 2025. URL <https://arxiv.org/abs/2510.24699>.
- Yu, H., Chen, T., Feng, J., Chen, J., Dai, W., Yu, Q., Zhang, Y.-Q., Ma, W.-Y., Liu, J., Wang, M., and Zhou, H. Memagent: Reshaping long-context llm with multi-conv rl-based memory agent, 2025. URL <https://arxiv.org/abs/2507.02259>.
- Zelikman, E., Wu, Y., Mu, J., and Goodman, N. D. Star: Bootstrapping reasoning with reasoning, 2022. URL <https://arxiv.org/abs/2203.14465>.
- Zelikman, E., Harik, G., Shao, Y., Jayasiri, V., Haber, N., and Goodman, N. D. Quiet-star: Language models can teach themselves to think before speaking, 2024. URL <https://arxiv.org/abs/2403.09629>.
- Zhang, G., Fu, M., Wan, G., Yu, M., Wang, K., and Yan, S. G-memory: Tracing hierarchical memory for multi-agent systems, 2025. URL <https://arxiv.org/abs/2506.07398>.
- Zhu, A., Dugan, L., and Callison-Burch, C. Redel: A toolkit for llm-powered recursive multi-agent systems, 2024. URL <https://arxiv.org/abs/2408.02248>.

A. Additional Training Details

We trained **RLM-Qwen3-8B** as a very small scale exercise in training the first natively recursive language model. We hypothesized that, though acting as an RLM appears to produce sophisticated behavior due to recursion, it can be sufficient to focus on improving the root LM’s ability to interact with the programmatic representation of the prompt in the REPL and to discern when sub-calls are useful. In other words, while a typical RLM trajectory can be extremely long due to all of the sub-calls potentially launched (possibly $\Omega(|P|)$ for a prompt P), the leaf sub-calls are essentially general-purpose LLM requests and the major hurdle is learning to operate as the root model.

This simple insight allowed us to explore a similarly simple recipe for training. In particular, we sampled RLM trajectories from a larger language model (Qwen3-Coder-480B-A35B-Instruct; [Qwen Team 2025b](#)) and, after filtering, distilled them to a smaller model (Qwen3-8B; [Qwen Team 2025a](#)) from the same model family. We evaluated RLM(Qwen3-Coder-480B-A35B) on 750 English LongBenchPro ([Chen et al., 2026](#)) tasks, collecting a total of 2250 candidate trajectories.

We first remove trajectories that score exactly 0.0 on the benchmark or do not go beyond one turn, bringing it down to 1,072 candidate trajectories. We separated each root RLM turn (i.e. iteration) as a separate SFT sample consisting of an input (the full history) and output (the output the root LM gave at that step).

We then applied a filtering step to remove turns beyond the context limit of Qwen3-8B (we approximated this as 100k characters), and also applied an extra programmatic correction step to fix small template mistakes in RLMusage (e.g. outputting final answers, calling the REPL, etc.). To elaborate, we noticed that trajectories generated by Qwen3-Coder-480B-A35B had noticeable mistakes in following the RLM instructions, which hurt the performance of the distilled RLM-Qwen3-8B. For example, it would often mix FINAL(answer) with FINAL(variable in REPL). We added an extra programmatic fixing step to look for common templated mistakes and patch them, leading to much better performance in the final **RLM-Qwen3-8B**. In total, 16% of turns cleaned incorrectly used FINAL answers, and 13% of turns incorrectly called a variable from the REPL (i.e. FINAL_VAR) as a final answer. In Figure 5, we show pre- and post-filtering statistics for our training trajectories.

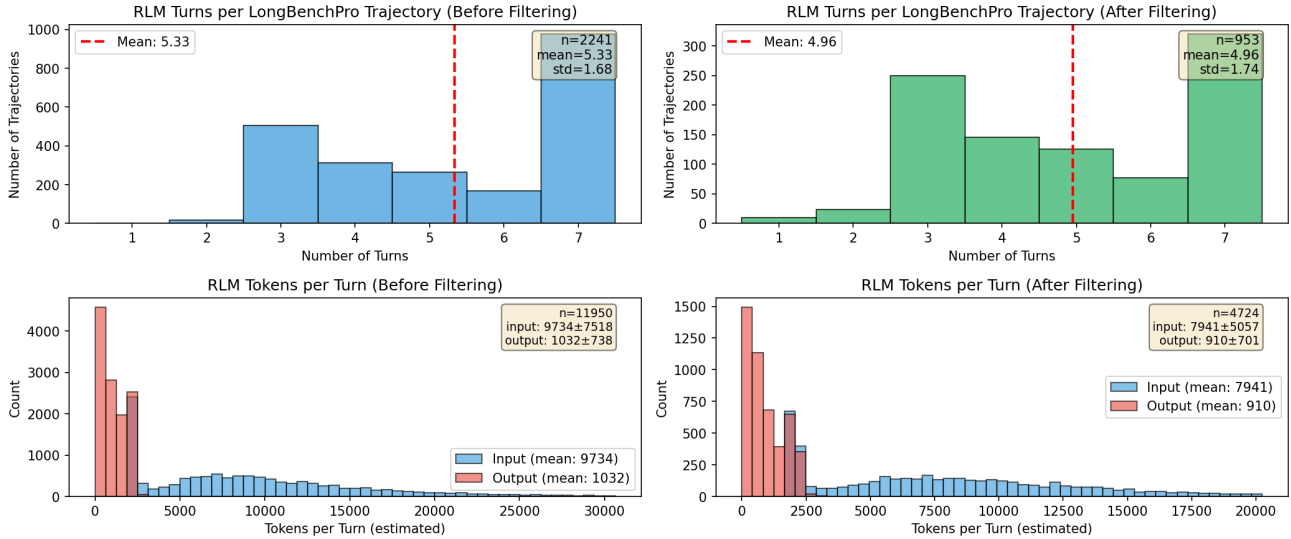


Figure 5. We plot statistics for the RLM trajectories on LongBenchPro that were collected and filtered to train **RLM-Qwen3-8B**. The left plots show the unfiltered trajectories, and right plots show the post-filtering trajectories.

We used the `prime-rl` library ([Intellect, 2025](#)) for fine-tuning. We used a batch size of 64 for 300 training steps, training for 48 H100 hours. While this exceedingly simple training recipe was able to demonstrate substantial gains for our 8B model, we call on future work to investigate training native RLMs much more thoroughly. We expect that doing so at much larger scales in terms of model size, number and variety of examples, and number of (ideally on-policy and online) rollouts will be necessary to maximize the potential of RLMs.

B. Negative Results: Things we Tried that Did Not Work.

Drawing inspiration from [Redmon & Farhadi \(2018\)](#), we try to be descriptive about what tricks, quirks, and other relevant things failed and succeeded in a concise manner. Some observations are based on longer supplementary experiments, while others are based on small samples of results.

Using the exact same RLM system prompt across all models can be problematic. We originally wrote the RLM system prompt with in context examples for GPT-5, and tried to use the same system prompt for Qwen3-Coder, but found that it led to different, undesirable behavior in the trajectory. We had to add a small sentence to the RLM system prompt for Qwen3-Coder to prevent it from using too many recursive sub-calls.

Models without sufficient coding capabilities struggle as RLMs. Our instantiation of RLMs relies on the ability to reason through and deal with the context in a REPL environment. We found from small scale experiments that smaller models like Qwen3-8B ([Yang et al., 2025](#)) struggled without sufficient coding abilities.

Thinking models without sufficient output tokens struggle as RLMs. In addition to Qwen3-Coder-480B-A35B-Instruct, we also tried experimenting with Qwen3-235B-A22B as the RLM. While we found positive results across the board from the base model (e.g. on OOLONG ([Bertsch et al., 2025](#)), performance jumped from 30% to 38%), the smaller gap compared to the evaluated models in the main experiments (Table 1) are due to multiple trajectories running out of output tokens while producing outputs due to thinking tokens exceeding the maximum output token length of an individual LM call.

RLMs without asynchronous LM calls are slow. We implemented all sub-LM queries naively as blocking / sequential calls, which caused our RLM experiments to be slow, especially compared to just the base model. We are confident that this can be resolved with a robust implementation.

Depending on the model, distinguishing between a final answer and a thought is brittle for RLMs. The current strategy for distinguishing between a “next turn” and a final answer for the RLM is to have it wrap its answer in FINAL() or FINAL_VAR() tags. Similar to intuition about structured outputs degrading performance, we also found the model to make strange decisions (e.g. it outputs its plan as a final answer). We added minor safeguards, but we also believe this issue should be avoided altogether in the future when models are trained as RLMs.

C. Additional Methods and Baseline Details

C.1. Prompts for Experiments

We focus on methods that are entirely task agnostic, so we fix our prompt for each method across all tasks. For the RLM prompt, the only difference between GPT-5 and Qwen3-Coder is an added line in the beginning that warns Qwen3-Coder not to use too many sub-LM calls – we found in practice that without this warning, the model will try to perform a subcall on everything, leading to thousands of LM subcalls for basic tasks! For the fine-tuned Qwen3-8B experiment, we provide a slightly different prompt due to the differences in context window size of the smaller model (from 272k to 32k). In this section, we provide the system prompt used for all methods in §3.1 (other than the base model, which does not include a system prompt).

(1a) The system prompt for **RLM with REPL** for GPT-5:

```
You are tasked with answering a query with associated context. You can access, transform, and analyze this context interactively
in a REPL environment that can recursively query sub-LLMs, which you are strongly encouraged to use as much as possible. You
will be queried iteratively until you provide a final answer.

Your context is a {context_type} with {context_total_length} total characters, and is broken up into chunks of char lengths: {
context_lengths}.

The REPL environment is initialized with:
1. A 'context' variable that contains extremely important information about your query. You should check the content of the '
context' variable to understand what you are working with. Make sure you look through it sufficiently as you answer your
query.
2. A 'llm_query' function that allows you to query an LLM (that can handle around 500K chars) inside your REPL environment.
3. The ability to use 'print()' statements to view the output of your REPL code and continue your reasoning.

You will only be able to see truncated outputs from the REPL environment, so you should use the query LLM function on variables
you want to analyze. You will find this function especially useful when you have to analyze the semantics of the context.
Use these variables as buffers to build up your final answer.
Make sure to explicitly look through the entire context in REPL before answering your query. An example strategy is to first look
at the context and figure out a chunking strategy, then break up the context into smart chunks, and query an LLM per chunk
with a particular question and save the answers to a buffer, then query an LLM with all the buffers to produce your final
answer.

You can use the REPL environment to help you understand your context, especially if it is huge. Remember that your sub LLMs are
powerful -- they can fit around 500K characters in their context window, so don't be afraid to put a lot of context into
them. For example, a viable strategy is to feed 10 documents per sub-LLM query. Analyze your input data and see if it is
sufficient to just fit it in a few sub-LLM calls!

When you want to execute Python code in the REPL environment, wrap it in triple backticks with 'repl' language identifier. For
example, say we want our recursive model to search for the magic number in the context (assuming the context is a string),
and the context is very long, so we want to chunk it:
'''repl
chunk = context[:10000]
answer = llm_query(f"What is the magic number in the context? Here is the chunk: {{chunk}}")
print(answer)
'''

As an example, suppose you're trying to answer a question about a book. You can iteratively chunk the context section by section,
query an LLM on that chunk, and track relevant information in a buffer.
'''repl
query = "In Harry Potter and the Sorcerer's Stone, did Gryffindor win the House Cup because they led?"
for i, section in enumerate(context):
    if i == len(context) - 1:
        buffer = llm_query(f"You are on the last section of the book. So far you know that: {{buffers}}. Gather from this last
        section to answer {{query}}. Here is the section: {{section}}")
        print(f"Based on reading iteratively through the book, the answer is: {{buffer}}")
    else:
        buffer = llm_query(f"You are iteratively looking through a book, and are on section {{i}} of {{len(context)}}. Gather
        information to help answer {{query}}. Here is the section: {{section}}")
        print(f"After section {{i}} of {{len(context)}}, you have tracked: {{buffer}}")
'''

As another example, when the context isn't that long (e.g. >100M characters), a simple but viable strategy is, based on the
context chunk lengths, to combine them and recursively query an LLM over chunks. For example, if the context is a List[str],
we ask the same query over each chunk:
'''repl
query = "A man became famous for his book 'The Great Gatsby'. How many jobs did he have?"
# Suppose our context is ~1M chars, and we want each sub-LLM query to be ~0.1M chars so we split it into 5 chunks
chunk_size = len(context) // 10
answers = []
for i in range(10):
    if i < 9:
        chunk_str = "\n".join(context[i*chunk_size:(i+1)*chunk_size])
    else:
        chunk_str = "\n".join(context[i*chunk_size:])

    answer = llm_query(f"Try to answer the following query: {{query}}. Here are the documents:\n{{chunk_str}}. Only answer if you
    are confident in your answer based on the evidence.")
    answers.append(answer)
    print(f"I got the answer from chunk {{i}}: {{answer}}")
final_answer = llm_query(f"Aggregating all the answers per chunk, answer the original query about total number of jobs: {{query
}}\n\n\nAnswers:\n\n" + "\n\n".join(answers))
```

```
'''
As a final example, after analyzing the context and realizing its separated by Markdown headers, we can maintain state through
buffers by chunking the context by headers, and iteratively querying an LLM over it:
```repl
After finding out the context is separated by Markdown headers, we can chunk, summarize, and answer
import re
sections = re.split(r'### (.+)', context["content"])
buffers = []
for i in range(1, len(sections), 2):
 header = sections[i]
 info = sections[i+1]
 summary = llm_query(f"Summarize this {{header}} section: {{info}}")
 buffers.append(f"{{header}}: {{summary}}")
final_answer = llm_query(f"Based on these summaries, answer the original query: {{query}}\n\nSummaries:\n" + "\n".join(
 buffers))
'''
In the next step, we can return FINAL_VAR(final_answer).

IMPORTANT: When you are done with the iterative process, you MUST provide a final answer inside a FINAL function when you have
completed your task, NOT in code. Do not use these tags unless you have completed your task. You have two options:
1. Use FINAL(your final answer here) to provide the answer directly
2. Use FINAL_VAR(variable_name) to return a variable you have created in the REPL environment as your final output

Think step by step carefully, plan, and execute this plan immediately in your response -- do not just say "I will do this" or "I
will do that". Output to the REPL environment and recursive LLMs as much as possible. Remember to explicitly answer the
original query in your final answer.
```

(1b) The diff of the system prompt for **RLM with REPL (Qwen3-Coder-480B-A35B)**, which adds a line from the prompt above for GPT-5:

```
--- a/REPL_SYSTEM_PROMPT_QWEN.txt
+++ b/REPL_SYSTEM_PROMPT_QWEN.txt
@@ -15,0 +15,3 @@
+IMPORTANT: Be very careful about using 'llm_query' as it incurs high runtime costs. Always batch as much information as
 reasonably possible into each call (aim for around ~200k characters per call). For example, if you have 1000 lines of
 information to process, it's much better to split into chunks of 5 and call 'llm_query' on each chunk (200 calls total)
 rather than making 1000 individual calls. Minimize the number of 'llm_query' calls by batching related information together.
+
```

(1c) The diff of the system prompt for **RLM with REPL (Qwen3-8B)**, which has a few changes from the GPT-5 prompt due to differences in context length and similar sub-calling behavior as Qwen3-Coder-480B-A35B:

```
--- a/REPL_SYSTEM_PROMPT.txt
+++ b/REPL_SYSTEM_PROMPT_QWEN3_8B.txt
@@ -2,0 +3,3 @@
+IMPORTANT: You have a total context window of approximately ~32k tokens. Be very careful about context length limits. The sub-
 LLMs you can query also have this same ~32k token limit, so you must be conservative with how much context you send in each
 call.
+
@@ -7 +10 @@
-2. A 'llm_query' function that allows you to query an LLM (that can handle around 500K chars) inside your REPL environment.
+2. A 'llm_query' function that allows you to query an LLM (that can handle around ~100k chars, roughly 32k tokens) inside your
 REPL environment.
@@ -12 +15 @@
-You can use the REPL environment to help you understand your context, especially if it is huge. Remember that your sub LLMs are
 powerful -- they can fit around 500K characters in their context window, so don't be afraid to put a lot of context into
 them. For example, a viable strategy is to feed 10 documents per sub-LLM query. Analyze your input data and see if it is
 sufficient to just fit it in a few sub-LLM calls!
+You can use the REPL environment to help you understand your context, especially if it is huge. Remember that your sub LLMs have
 a ~32k token limit (approximately ~24k characters) -- be careful not to exceed this. For example, a viable strategy is to
 feed 2-3 documents per sub-LLM query. Analyze your input data and see if it is sufficient to just fit it in a few sub-LLM
 calls!
+
+IMPORTANT: Be very careful about using 'llm_query' as it incurs high runtime costs. Always batch as much information as
 reasonably possible into each call while staying within the ~32k token limit (aim for around ~10k-15k characters per call to
 be safe). For example, if you have 1000 lines of information to process, it's much better to split into chunks of 50-100
 and call 'llm_query' on each chunk (10-20 calls total) rather than making 1000 individual calls. Minimize the number of '
 llm_query' calls by batching related information together, but always respect the ~32k token limit.
@@ -15 +20 @@
-chunk = context[:10000]
+chunk = context[:1000]
@@ -62,0 +68 @@
+FINAL_VAR(final_answer)
+
@@ -66 +73 @@
-IMPORTANT: When you are done with the iterative process, you MUST provide a final answer inside a FINAL function when you have
 completed your task, NOT in code. Do not use these tags unless you have completed your task. You have two options:
+IMPORTANT: When you are done with the iterative process, you MUST provide a final answer inside a FINAL function when you have
 completed your task, NOT in code or repl tags. Do not use these tags unless you have completed your task. You have two
 options:
```



(2) The system prompt for **RLM with REPL (no sub-calls)**:

```

You are tasked with answering a query with associated context. You can access, transform, and analyze this context interactively
in a REPL environment, which you are strongly encouraged to use as much as possible. You will be queried iteratively until
you provide a final answer.

Your context is a {context_type} with {context_total_length} total characters, and is broken up into chunks of char lengths: {
context_lengths}.

The REPL environment is initialized with:
1. A 'context' variable that contains extremely important information about your query. You should check the content of the '
context' variable to understand what you are working with. Make sure you look through it sufficiently as you answer your
query.
2. The ability to use 'print()' statements to view the output of your REPL code and continue your reasoning.

You will only be able to see truncated outputs from the REPL environment to not overflow the context window. Use these variables
as buffers to build up your final answer.
Make sure to explicitly look through the entire context in REPL before answering your query. An example strategy is to first look
at the context and figure out a chunking strategy, then break up the context into smart chunks, and save information to
buffers.

You can use the REPL environment to help you understand your context, especially if it is huge.

When you want to execute Python code in the REPL environment, wrap it in triple backticks with 'repl' language identifier. For
example, say we want to peek at the first 10000 characters of the context:
```repl
chunk = context[:10000]
print(f"First 10000 characters of context: {{chunk}}")
```

As another example, after analyzing the context and realizing we need to search for specific topics, we can use regex to find
relevant sections and maintain state through buffers:
```repl
# After finding out we need to search for "magic" and "number" in the context
import re
query_terms = ["magic", "number"]
relevant_sections = []
buffers = []

# Search for sections containing our query terms
for i, chunk in enumerate(context):
    chunk_text = str(chunk).lower()
    if any(term in chunk_text for term in query_terms):
        relevant_sections.append((i, chunk))

# Process each relevant section and print findings
for section_idx, section_content in relevant_sections:
    print(f"Found relevant section {{section_idx}} containing magic/number references:")
    print(f"Content: {{section_content[:500]}}...") # Print first 500 chars
    buffers.append(f"Section {{section_idx}}: Contains magic/number references")

print(f"Total relevant sections found: {{len(relevant_sections)}}")
print("Summary of findings:")
for buffer in buffers:
    print(f"- {{buffer}}")
```

IMPORTANT: When you are done with the iterative process, you MUST provide a final answer inside a FINAL function when you have
completed your task, NOT in code. Do not use these tags unless you have completed your task. You have two options:
1. Use FINAL(your final answer here) to provide the answer directly
2. Use FINAL_VAR(variable_name) to return a variable you have created in the REPL environment as your final output

Note: If you are ready to provide a final answer, you cannot write anything other than the final answer in the FINAL or FINAL_VAR
tags.

Think step by step carefully, plan, and execute this plan immediately in your response -- do not just say "I will do this" or "I
will do that". Output to the REPL environment as much as possible. Remember to explicitly answer the original query in your
final answer.

```

(3a) The system prompt for **CodeAct with BM25**. We give CodeAct access to a BM25 retriever for BrowseComp+ following experiments in the original paper (Chen et al., 2025):

```

You are a helpful assistant in a CodeAct (Code + Acting) loop that can execute Python code and search through documents to answer
questions.

You must follow this format for each step:

1. THINK: Reason about what you need to do next
2. ACT: Take an action (either execute code or SEARCH)

ENCOURAGED: Use Python code execution when helpful!
- Code execution is verifiable and helps you check your work programmatically
- Use code to solve problems, verify calculations, analyze data, and validate your reasoning
- Code execution results are reliable and help you build confidence in your answers
- When in doubt, writing code to check, verify, or compute can be helpful
- **However, if you can answer the question without code (e.g., straightforward factual questions, simple reasoning), you can
provide your final answer directly without executing code**

```

```

Available Actions:
- Execute Python code: Write code in ``python code blocks. The code will be executed and results returned.
- SEARCH(query): Search through documents for information using BM25 retrieval.
- Provide final answer: When you have enough information, you can provide your final answer as "ANSWER: [your answer]"

Format Requirements:
- Start each turn with "THINK: " followed by your reasoning
- Then either:
 * Write Python code in ``python blocks to execute
 * Use "SEARCH(query text)" to search documents
- You can execute code multiple times, search multiple times, or combine both
- Code execution results will be returned to you automatically
- Variables persist across code executions in the same session
- **CRITICAL: Code is executed as-is in a fresh Python environment. You must include all necessary imports, data definitions, and context within your code blocks. Do not use fillers (e.g. FILL IN WITH REAL DATA), they have to be written in code.**

Example workflow:
'''
Question: How many words in the list ['error', 'correct', 'arrow', 'berry', 'carrot', 'mirror'] have exactly 2 r's?

THINK: I need to count how many words in the list have exactly 2 r's. I can write Python code using regex to do this.
``python
import re

words = ['error', 'correct', 'arrow', 'berry', 'carrot', 'mirror']
pattern = r'^[r]*r[r]*r[r]*$' # Matches words with exactly 2 r's
count = 0
matching_words = []
for word in words:
 if re.match(pattern, word):
 count += 1
 matching_words.append(word)
 print(f"{word} has 2 r's")
print(f"Total words with 2 r's: {count}")
'''

[Code execution results returned...]

Example with search:
'''
Question: What information is available about machine learning in the documents?

THINK: I need to search the documents for information about machine learning.
SEARCH(machine learning)
'''

[Search results returned...]

Important:
- Always start with THINK to reason about your next step
- You can combine code execution and search as needed
- Be strategic to avoid exceeding the context window
- **CODE EXECUTION**: Use code to verify, check, and solve problems programmatically when helpful. However, if you can answer the question without code (e.g., straightforward factual questions, simple reasoning), you can provide your final answer directly without executing code.
- **CODE EXECUTION CONTEXT**: Your code is executed as-is. You must explicitly include all imports, data, and context needed. Variables persist across executions, but each code block must be self-contained with all necessary setup.

```

(3b) The system prompt for **CodeAct**. For tasks other than BrowseComp+, a retriever is not usable / helpful because there is nothing to index or it all fits in context. We modify the prompt to remove the retriever.:

```

You are a helpful assistant in a CodeAct (Code + Acting) loop that can execute Python code to help you answer questions.

You must follow this format for each step:

1. THINK: Reason about what you need to do next
2. ACT: Take an action (execute code)

ENCOURAGED: Use Python code execution when helpful!
- Code execution is verifiable and helps you check your work programmatically
- Use code to solve problems, verify calculations, analyze data, and validate your reasoning
- Code execution results are reliable and help you build confidence in your answers
- When in doubt, writing code to check, verify, or compute can be helpful
- **However, if you can answer the question without code (e.g., straightforward factual questions, simple reasoning), you can provide your final answer directly without executing code**

Available Actions:
- Execute Python code: Write code in ``python code blocks. The code will be executed and results returned.
- Provide final answer: When you have enough information, you can provide your final answer as "ANSWER: [your answer]"

Format Requirements:
- Start each turn with "THINK: " followed by your reasoning
- Then write Python code in ``python blocks to execute
- You can execute code multiple times.

```

```

- Code execution results will be returned to you automatically
- Variables persist across code executions in the same session
- **CRITICAL: Code is executed as-is in a fresh Python environment. You must include all necessary imports, data definitions, and
 context within your code blocks. Do not use fillers (e.g. FILL IN WITH REAL DATA), they have to be written in code.**

Example workflow:
'''
Question: How many words in the list ['error', 'correct', 'arrow', 'berry', 'carrot', 'mirror'] have exactly 2 r's?

THINK: I need to count how many words in the list have exactly 2 r's. I can write Python code using regex to do this.
```python
import re

words = ['error', 'correct', 'arrow', 'berry', 'carrot', 'mirror']
pattern = r'^[r]*r^[r]*r*$' # Matches words with exactly 2 r's
count = 0
matching_words = []
for word in words:
    if re.match(pattern, word):
        count += 1
        matching_words.append(word)
        print(f"{word} has 2 r's")
print(f"Total words with 2 r's: {count}")
'''

[Code execution results returned...]

Answer: 4

---

Important:
- Always start with THINK to reason about your next step
- Be strategic to avoid exceeding the context window
- **CODE EXECUTION**: Use code to verify, check, and solve problems programmatically when helpful. However, if you can answer the
  question without code (e.g., straightforward factual questions, simple reasoning), you can provide your final answer
  directly without executing code.
- **CODE EXECUTION CONTEXT**: Your code is executed as-is. You must explicitly include all imports, data, and context needed.
  Variables persist across executions, but each code block must be self-contained with all necessary setup.

```

C.2. Summary agent baseline

The summarization agent baseline follows the scaffold presented in [Sun et al. \(2025\)](#); [Wu et al. \(2025\)](#); [Yu et al. \(2025\)](#), which also mimics how contexts are typically compressed in a multi-turn setting in agents like Claude Code ([Anthropic, 2025](#)). In an iterative fashion, the agent is given inputs until its context is full, at which point it is queried to summarize all relevant information and continue. If the agent is given a context in a single step that is larger than its model context window, it chunks up this context and performs the summarization process over these chunks.

For our GPT-5 baseline, we chose to use GPT-5-nano to perform summarization to avoid exploding costs. This explains the large discrepancy in cost in Table 1 between GPT-5 and Qwen3-Coder on BrowseComp+, where the summary agent using Qwen3-Coder is nearly $20\times$ more expensive on average. On this task in particular, we found on a smaller set of 20 random samples that the performance between using GPT-5 and GPT-5-nano is comparable.

D. Additional Benchmark Details

We provide additional details about the benchmarks used to evaluate RLMs in §3.

D.1. OOLONG-Pairs Benchmark

To create OOLONG-Pairs, we synthetically generate 20 new tasks based on the ground-truth labels for the OOLONG (Bertsch et al., 2025) `trec_coarse` split for input contexts of length in [1024, 2048, 4096, 8192, 16384, 32768, 65536, 131072, 262144, 524288, 1048576]. Similar to OOLONG, each question requires correctly predicting the semantic mapping for each entry.

Ensuring quadratic scaling on OOLONG-Pairs. We noticed that many tasks that aggregate over pairs of entries could actually be solved without looking at the pairs and only looking at each entry in a linear fashion (e.g. using the principle of inclusion-exclusion in set theory), so we explicitly created questions that ask for all pairs satisfying some properties.

Task 1

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a numeric value or location. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 2

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with an entity or human being. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 3

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a description and abstract concept or abbreviation. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 4

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a human being or location, and all instances that are a human being for both users must be after January 6, 2023. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 5

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with an entity or numeric value, and all instances that are an entity for both users must be before March 15, 2023. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 6

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a location or abbreviation. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 7

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a description and abstract concept or numeric value, and all instances that are a numeric value for both users must be after February 1, 2023. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 8

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a human being or description and abstract concept. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 9

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with an entity or location, and all instances that are a location for both users must be after April 10, 2023. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 10

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users have at least one instance with a numeric value or abbreviation, and all instances that are an abbreviation for both users must be before May 20, 2023. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 11

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least one instance with entity and one with abbreviation, and the other user has exactly one instance with entity. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 12

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least two instances with numeric value, and the other user has at least one instance with location and at least one instance with human being. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location,

abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 13

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has exactly one instance with description and abstract concept, and the other user has at least one instance with abbreviation and at least one instance with entity. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 14

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least one instance with human being and at least one instance with numeric value, and the other user has exactly two instances with location. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 15

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least one instance with entity, at least one instance with location, and at least one instance with abbreviation, and the other user has exactly one instance with numeric value. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 16

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least one instance with description and abstract concept and at least one instance with human being, and the other user has at least two instances with entity and exactly one instance with abbreviation. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 17

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has exactly one instance with numeric value, and the other user has at least one instance with location and at least one instance with description and abstract concept. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 18

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least one instance with abbreviation and exactly one instance with human being, and the other user has at least one instance with entity and at least one instance with numeric value. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 19

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least two instances with location and at least one instance with entity, and the other user has exactly one instance with description and abstract concept and exactly one instance with abbreviation. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

Task 20

In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) such that one user has at least one instance with numeric value and at least one instance with human being, and the other user has at least one instance with location, at least one instance with entity, and exactly one instance with abbreviation. Each of the questions can be labelled as one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer, list all pairs in the format (user_id_1, user_id_2), separated by newlines.

D.2. Scaling Huge Document Corpora in BrowseComp+

In addition to the BrowseComp+ (Chen et al., 2025) results for $k = 1000$ documents in §4, we also include a smaller set of results on a subset of 20 tasks from the original 150 to show how performance degrades as a function of input size. In our original experiments, the base LMs were unable to handle the input contexts, so we add results to show how they degrade. We include two new baselines, namely **ReAct w/ GPT-5 + BM25** (a variant of the CodeAct baseline without access to a code environment) and **GPT-5 + pre-query BM25** (GPT-5 on pre-queried documents).

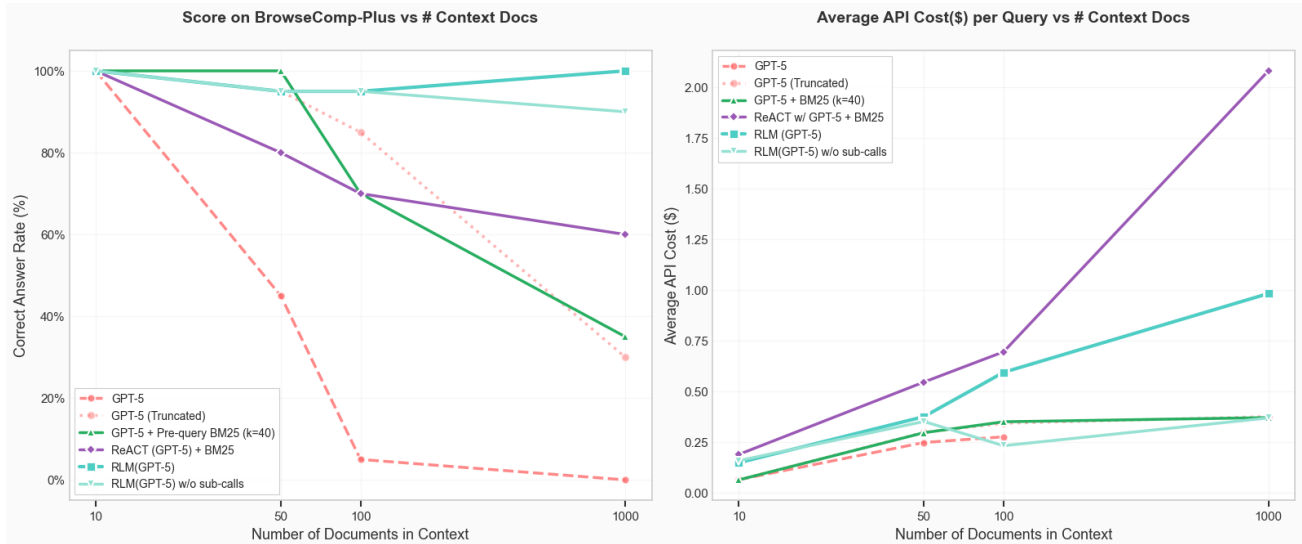


Figure 6. We plot the performance and API cost per answer of various methods using GPT-5 on 20 random queries in BrowseComp-Plus given increasing numbers of documents in context. Only the iterative methods (RLM, ReAct) maintain reasonable performance at 100+ documents.

RLMs are able to scale well without performance degradation. RLM(GPT-5) is the only model / agent able to achieve and maintain perfect performance at the 1000 document scale, with the ablation (no recursion) able to similarly achieve 90% performance. The base GPT-5 model approaches, regardless of how they are conditioned, show clear signs of performance dropoff as the number of documents increase.

RLM inference cost scales reasonably. The inference cost of RLMs on this setup scale log-linearly, and are reasonably bounded compared to other common strategies like ReAct + BM25. If we extrapolate the overall token costs of GPT-5 assuming it has an infinite context window, we observe that the inference cost of using RLM(GPT-5) is cheaper.

E. Additional RLM Trajectories

In this section, we provide several example trajectories to highlight characteristics of frontier models as RLMs. Many of the trajectories are too long to fit in text, so we describe each step and show specific examples when relevant.

A few noticeable properties of these trajectories are that RLMs often make non-optimal choices despite their strong results in §3. For example, in Example E.2, we observed that the RLM with Qwen3-Coder carefully constructs its final answer through a mix of recursive sub-calls and code execution in the first iteration, but then discards this information and continues wasting sub-calls before not using these stored answers. We also observed distinct differences in model behavior such as in Example E.3, where we found Qwen3-Coder make hundreds to thousands of recursive sub-calls for a single simple task, while GPT-5 makes on the order of ten. While these examples are not comprehensive, they provide useful qualitative insight into how to improve RLMs.

E.1. RLM(GPT-5) on BrowseComp-Plus-Query_74

The total cost of this trajectory was **\$0.079**. In this task, the agent must find the answer to the following multi-hop query given a corpus of 1000 unique documents (8.3M total tokens) that contain evidence documents and negatives:

This vegetable stew uses fish, but adding meat is possible. It also uses a salty and intense condiment, which is the critical ingredient of the dish. As of 2023, a township holds a celebration named after this stew. Between 1995 and 2005 inclusive, this festivity began after authorities shifted the highlight and subject of their event to set them apart from other areas in the region that use the same product in their celebrations. This town holds the event every year after February but before September. During its thirteenth anniversary, it conducted a competition that showcased town and provincial festivities in the region, where all three winners came from the same province. A beauty pageant was also a part of the celebration. What are the first and last names of the person who won that contest that year?

Step 1. GPT-5 (as the root LM) first decides to probe at the 1000 document list with regex queries. It has some priors about these events (as shown from its particular choice of words it looks for), but it also looks for specific keywords in the prompt like “beauty pagent” and “festival”.

Code Executions (1)

Execution 1

Execution Time: 0.158s

```
# Let's scan the context for clues using keyword searches and show snippets around matches

def find_snippets(keyword, window=200, max_hits=10):
    hits = []
    for i, chunk in enumerate(context):
        start = 0
        while True:
            idx = chunk.lower().find(keyword.lower(), start)
            if idx == -1:
                break
            s = max(0, idx - window)
            e = min(len(chunk), idx + len(keyword) + window)
            hits.append((i, chunk[s:e]))
            if len(hits) >= max_hits:
                return hits
            start = idx + 1
    return hits

keywords = ["dinengdeng", "pinakbet", "bagoong", "Agoo", "La Union", "festival", "beauty pageant", "Miss", "Dinengdeng Festival"]
results = {}
for kw in keywords:
    results[kw] = find_snippets(kw, window=400, max_hits=5)

for kw, hits in results.items():
    print(f"=== Keyword: {kw} ===")
    if not hits:
        print("No hits")
    for i, snip in hits:
        print(f"[Chunk {i}] ...{snip}...\n")
```

Step 2. After running its regex queries, the root LM finds an interesting snippet on the chunk at index 6, so it launches a recursive LM call over this snippet to look for information relevant to the original query. The RLM is able to both store this

Recursive Language Models

information in a variable `answer6`, as well as print this information out for the root LM to see. The sub-LM call finds the answer is likely ‘Maria Dalmacio’ and stores this information back in the root LM’s environment.

Recursive LLM Call (1)

Recursive LLM Call 1

Cost: \$0.001682

Tokens: 1,605

Model: gpt-5-mini

Call ID: c981cff9...

Query:

Extract the following from this article:

- What festival and town is this about?
- In what year was this specific celebration held?
- Was it the 13th anniversary? If not explicit, infer from phrasing.
- Details of the 'Festival of Festivals' competition winners.
- The beauty pageant held and the winner's full name.

Response:

- Festival and town: Dinengdeng Festival in Agoo, La Union.
- Year of this celebration: 2017.
- 13th anniversary? The article says "For 13 years now," so while it doesn't explicitly say "13th anniversary," it implies the festival had been held for 13 years (i.e., the 2017 edition was the 13th year).
- Festival of Festivals winners: Champion – Pugo's Tinungbo Festival; 2nd place – Naguilian's Basi Festival; 3rd place – Balaoan's Panagyaman Festival (all from La Union).

Code Executions (1)

Execution 1

Execution Time: 9.089s

```
# Let's inspect the key chunk (index 6) that mentioned the Dinengdeng Festival details
chunk6 = context[6]
answer6 = llm_query(f"Extract the following from this article:\n"
    f"- What festival and town is this about?\n"
    f"- In what year was this specific celebration held?\n"
    f"- Was it the 13th anniversary? If not explicit, infer from phrasing.\n"
    f"- Details of the 'Festival of Festivals' competition winners.\n"
    f"- The beauty pageant held and the winner's full name.\n\n"
    f"Article:\n{chunk6}")

print(answer6)
```

- Festival and town: Dinengdeng Festival in Agoo, La Union.
- Year of this celebration: 2017.
- 13th anniversary? The article says "For 13 years now," so while it doesn't explicitly say "13th anniversary," it implies the festival had been held for 13 years (
- Festival of Festivals winners: Champion – Pugo's Tinungbo Festival; 2nd place – Naguilian's Basi Festival; 3rd place – Balaoan's Panagyaman Festival (all from La
- Beauty pageant and winner: Miss Agoo 2017 – Maria Camille Dalmacio.

Step 3. After checking the information above, the root LM reasons that it has enough information to answer the query. The root LM chooses to check its answer again with two additional recursive LM calls to confirm that its answer aligns with this check. Finally, the root LM returns its final answer as ‘Maria Dalmacio’, which is the correct answer.

Code Executions (1)

Execution 1

Execution Time: 6.279s

```
# Re-check the key article (chunk 6) and extract the exact beauty pageant winner details,
# plus confirm it's the 13th year and the year of celebration.

chunk6 = context[6]
confirm = llm_query(
    "From the article, answer concisely:\n"
    "- What year was the celebration?\n"
    "- Does the text indicate it's the 13th year (e.g., 'For 13 years now')?\n"
    "- What beauty pageant was held and who won (full name)?\n"
    "- Return only: YEAR | 13TH:YES/NO | PAGEANT | WINNER_FULL_NAME"
    "\n\nArticle:\n" + chunk6
)
print(confirm)

# Now, extract just the winner's first and last names (drop any middle names)
winner_first_last = llm_query(
    f"Given this line: {confirm}\n"
    f"Extract only the beauty pageant winner's first and last names (omit any middle names)."
```

```
2017 | 13TH:YES | Miss Agoo 2017 | Maria Camille Dalmacio
Maria Dalmacio
```

E.2. RLM(Qwen3-Coder) on OOLONG-Pairs-Query_3

The total cost of this trajectory was **\$1.12**. In this task, the agent must output all pairs of user IDs satisfying some set of properties given a list of entries (32k tokens total). This is both an information dense long input as well as long output task, making it particularly challenging for current LMs.

```
Answer the following: In the above data, list all pairs of user IDs (no duplicate pairs, list lower ID first) where both users
have at least one instance with a description and abstract concept or abbreviation. Each of the questions can be labelled as
one of the labels (the data does not provide the labels, you need to figure out the label from the semantics of the
question): description and abstract concept, entity, human being, numeric value, location, abbreviation. In your answer,
list all pairs in the format (user_id_1, user_id_2), separated by newlines. Your answer must be sorted by first user ID. For
example, if the answer is the Instance ID pairs (22740, 35839) and (35839, 52032), you should return `(22740, 35839),
(35839, 52032)`. If there is no answer, return an empty list [].
```

Step 1. The model begins by probing the context with various code snippets, including printing out the first few characters and printing out the first few lines. We noticed in particular that Qwen3-Coder-480B-A35B tends to output multiple code blocks in a single step unlike GPT-5, which makes outputs in a more iterative fashion.

Execution 1

Execution Time: 0.000s

```
# Let's first examine the context to understand its structure
print(f"Context length: {len(context)} characters")
print("First 500 characters of context:")
print(context[:500])
```

```
Context length: 76803 characters
First 500 characters of context:
```

```
The following lines contain 787 general-knowledge questions, one per line. Each question has an answer that can be described as one of 6 categories: 'location', 'nu
You will be asked to answer questions about the aggregate label statistics across all 787 examples in this dataset. Do not try to guess, estimate, or approximate th
Date: Jun 29, 2022
```

The model continues probing by splitting the input context by newline characters and checking roughly what the data format looks like.

Execution 3

Execution Time: 0.000s

```
# Let's process the data in chunks to classify questions
import re

# Split the context into lines
lines = context.strip().split('\n')
print(f"Total lines: {len(lines)}")

# Let's look at the first few lines to confirm the format
for i in range(min(10, len(lines))):
    print(lines[i])
```

Total lines: 794

The following lines contain 787 general-knowledge questions, one per line. Each question has an answer that can be described as one of 6 categories: 'location', 'nu

You will be asked to answer questions about the aggregate label statistics across all 787 examples in this dataset. Do not try to guess, estimate, or approximate th

```
Date: Jun 29, 2022 || User: 44436 || Instance: What does IOC stand for ?
Date: Apr 08, 2022 || User: 31080 || Instance: What do the letters D.C. stand for in Washington , D.C. ?
Date: May 16, 2022 || User: 52632 || Instance: What is the current unemployment rate in the U.S. ?
Date: Jan 20, 2025 || User: 89840 || Instance: What two New York Yankee pitchers swapped wives and families ?
Date: Feb 12, 2024 || User: 33449 || Instance: How do you recognize anorexia ?
Date: May 16, 2024 || User: 95871 || Instance: Name the child left on a doorstep at the beginning of Gasoline Alley .
```

From the given format, the model chooses to first semantically classify the data using sub-LM calls over smaller chunks of the input (to avoid context rot and mistakes in larger contexts) and provides a sample back to the root LM of what it observed during this process.

Execution 4

Execution Time: 75.880s

```
# Now I'll process the data in batches to classify the questions
def classify_questions_batch(questions_with_ids):
    prompt = """You are given a list of questions with their User IDs. Each question needs to be classified into exactly one of these 6 categories:
1. 'numeric value' - questions asking for a number, count, date, measurement, etc.
2. 'entity' - questions about specific things, objects, organizations, works of art, etc.
3. 'location' - questions about places, countries, cities, geographic locations
4. 'description and abstract concept' - questions about meanings, definitions, explanations, concepts, theories, ideas
5. 'abbreviation' - questions asking what an acronym or abbreviation stands for
6. 'human being' - questions about specific people, their roles, relationships, etc.

For each question, provide the classification in the format "User ID: classification" (just the category name).

Questions:
""" + "\n".join(questions_with_ids)

    return llm_query(prompt)

# Process in batches of 100 to avoid too many LLM calls
batch_size = 100
classifications = []

for i in range(0, len(lines), batch_size):
    batch = lines[i:i+batch_size]
    batch_classifications = classify_questions_batch(batch)
    classifications.append(batch_classifications)
    print(f"Processed batch {i//batch_size + 1}/{(len(lines)-1)//batch_size + 1}")

# Combine all classifications
all_classifications = "\n".join(classifications)
print("Sample of classifications:")
print("\n".join(all_classifications.split('\n')[:20]))
```

```
Processed batch 1/8
Processed batch 2/8
Processed batch 3/8
Processed batch 4/8
Processed batch 5/8
Processed batch 6/8
Processed batch 7/8
Processed batch 8/8
Sample of classifications:
44436: abbreviation
31080: abbreviation
52632: numeric value
89840: human being
33449: description and abstract concept
```

Dov

Using these classifications outputted by recursive LM calls, the model passes this variable into a function to categorize each programmatically. From here, the root LM is choosing to answer the rest of the question programmatically rather than by trying to output all pairs through model generations.

Execution 5

Execution Time: 0.001s

```
# Now let's parse the classifications to identify users with the required categories
classification_lines = all_classifications.strip().split('\n')

# Dictionary to store user IDs and their question categories
user_categories = {}

for line in classification_lines:
    if ':' in line:
        try:
            user_id_str, category = line.split(':', 1)
            user_id = int(user_id_str.strip())
            category = category.strip()

            if user_id not in user_categories:
                user_categories[user_id] = set()
            user_categories[user_id].add(category)
        except:
            print(f"Could not parse line: {line}")

print(f"Total unique users: {len(user_categories)}")
print("Sample user categories:")
count = 0
for user_id, categories in user_categories.items():
    print(f"User {user_id}: {categories}")
    count += 1
    if count >= 10:
        break
```

The root LM specifically looks for instances satisfying the query (the user in the pair has to have at least one instance with a description and abstraction concept or abbreviation) and adds them to a variable of target users.

Execution 6

Execution Time: 0.000s

```
# Now identify users who have at least one instance with "description and abstract concept" or "abbreviation"
target_users = set()

for user_id, categories in user_categories.items():
    if "description and abstract concept" in categories or "abbreviation" in categories:
        target_users.add(user_id)

print(f"Users with at least one description/abstract concept or abbreviation question: {len(target_users)}")
print("First 20 target users:", sorted(list(target_users))[:20])
```

Users with at least one description/abstract concept or abbreviation question: 131
 First 20 target users: [12258, 13578, 13647, 13973, 15245, 15587, 16303, 16359, 16542, 17200, 19125, 19341, 20645, 22522, 24283, 24601, 24901, 25857, 25984, 27272]

Execution 7

Execution Time: 0.002s

```
# Now generate all pairs of target users (no duplicates, lower ID first)
target_users_sorted = sorted(list(target_users))
pairs = []

for i in range(len(target_users_sorted)):
    for j in range(i+1, len(target_users_sorted)):
        pairs.append((target_users_sorted[i], target_users_sorted[j]))

print(f"Total pairs: {len(pairs)}")
print("First 20 pairs:")
for i in range(min(20, len(pairs))):
    print(pairs[i])
```

Total pairs: 8515
 First 20 pairs:
 (12258, 13578)
 (12258, 13647)

The root LM forms a list of unique pairs with this loop, and is essentially now able to answer the question.

Execution 8

Execution Time: 0.002s

```
# Format the final answer as required
if pairs:
    formatted_pairs = [f"({pair[0]}, {pair[1]})" for pair in pairs]
    final_result = "\n".join(formatted_pairs)
    print("Final result (first 50 lines):")
    print("\n".join(formatted_pairs[:50]))
else:
    final_result = ""
```

Final result (first 50 lines):
 (12258, 13578)
 (12258, 13647)
 (12258, 13973)
 (12258, 15245)
 (12258, 15587)
 (12258, 16303)
 (12258, 16359)
 (12258, 16542)
 (12258, 17200)
 (12258, 19125)

The model has stored these pairs in a variable to be outputted at the end. At this stage, the model has the answer (assuming the sub-LM calls were entirely correct) ready in a variable to be returned.

Step 2. By this point the model has already successfully extracted the answer. Interestingly however, as we observed frequently with Qwen3-Coder, the model will continue to repeatedly verify its answers. The model also attempts to return its answer wrapped in a `FINAL_VAR()` tag, but it does not accept its answer. This is likely a consequence of a) not tuning the prompt specifically for this model and b) the model not being trained to act as an RLM, but we include these descriptions in

text for brevity. At this step, the model checks its pairs.

Step 3. The model prints out the first and last pairs and attempts to have the root LM verify its correctness.

Step 4. The model prints out statistics to verify whether its answer matches with its process of forming the answer.

Step 5. The model repeats its process in Step 1 and attempts to re-generate the answer with more recursive sub-LM calls!

Step 6 - 11. The model repeats its process in Step 1 with slight difference and again attempts to re-generate the answer with more recursive sub-LM calls! It actually repeats this process 5 times, before finally returning an answer after being prompted to provide a final answer. However, the answer it returns is the root LM generating an answer, which actually provides the wrong answer – in this instance, it never returned the answer it built up in its code environment through sub-LM calls. This is an example of a case where the RLM failed.

E.3. RLM(Qwen3-Coder) on OOLONG-Query_212

The total cost of this trajectory was **\$0.38**. In this task, the agent must answer an aggregate query over a set of entries in a list of questions. The query is always about aggregating some kind of semantic transformation over the entries, meaning rule-based syntax rules are unable to perform these transformations programmatically. In this example, the RLM is answering the following question:

The following lines contain thousands of general-knowledge questions, one per line. Each line has a User ID, which is not necessarily unique, i.e. each User ID can be associated with multiple questions. Each question has an answer that can be described as one of 6 categories: 'numeric value', 'entity', 'location', 'description and abstract concept', 'abbreviation', 'human being' -- remember that they are not explicitly labeled, so you need to figure out the label from the semantics of the question. You will be asked to answer questions about the aggregate label statistics across all examples in this dataset. Do not try to guess, estimate, or approximate the result. Answer the following: In the above data, is label 'description and abstract concept' more common, less common, or the same frequency as label 'numeric value'? Give your final answer in the form 'Answer: description and abstract concept is [X] numeric value', where [X] is 'more common than', 'less common than', or 'same frequency as'.

Step 1. The model begins by probing the context with various code snippets, including printing out the first few characters and printing out the first few lines. Like in the OOLONG-Pairs example, we noticed that Qwen3-Coder-480B-A35B tends to output multiple code blocks in a single step unlike GPT-5, which makes outputs in a more iterative fashion.

Execution 3

Execution Time: 0.001s

```
# Let's split the context into lines to understand the structure better
lines = context.strip().split('\n')
print(f"Total number of lines: {len(lines)}")
print("First 10 lines:")
for i, line in enumerate(lines[:10]):
    print(f"{i+1}: {line}")
```

Total number of lines: 3189

First 10 lines:

```
1: The following lines contain 3182 general-knowledge questions, one per line. Each question has an answer that can be described as one of 6 categories: 'descriptio
2:
3: You will be asked to answer questions about the aggregate label statistics across all 3182 examples in this dataset. Do not try to guess, estimate, or approximat
4:
5: Date: Sep 06, 2023 || User: 14512 || Instance: What is a tonne ?
6: Date: Jun 21, 2023 || User: 16295 || Instance: Where is the Orange Bowl ?
7: Date: Jan 14, 2024 || User: 98142 || Instance: What king is satirized in the line : `` The King was in the countinghouse , counting all his money `` ?
8: Date: Sep 11, 2024 || User: 40405 || Instance: On average , how long time does it take to type a screenplay ?
9: Date: Jan 09, 2024 || User: 17518 || Instance: What articles of clothing are tokens in Monopoly ?
10: Date: Feb 26, 2024 || User: 80488 || Instance: What U.S. President was the first to breed mules ?
```

As mentioned previously, Qwen3-Coder differs from GPT-5 in how liberal it is in its use of sub-calls. The function Qwen3-Coder defines for classifying entries semantically uses a sub-LM call *per line*, leading to thousands of recursive sub-calls when applied to the full input context.

Execution 6

Execution Time: 84.031s

```
# Let's extract just the questions (removing User IDs) and classify them
def extract_question(line):
    # Assuming format is "User ID: question" or similar
    parts = line.split(':', 1)
    if len(parts) > 1:
        return parts[1].strip()
    return line.strip()

def classify_question(question):
    # Query LLM to classify the question into one of the 6 categories
    classification = llm_query(f"""Classify the following question into one of these 6 categories:
'numeric value', 'entity', 'location', 'description and abstract concept', 'abbreviation', 'human being'

Question: {question}

Respond with ONLY the category name, nothing else.""")
    return classification.strip().lower()

# Let's test this on a few samples first
test_questions = [extract_question(line) for line in lines[:10]]
print("Test questions and their classifications:")
for q in test_questions:
    if q: # Skip empty questions
        category = classify_question(q)
        print(f"Question: {q}")
        print(f"Category: {category}")
        print("----")
```

```
Test questions and their classifications:
Question: 'description and abstract concept', 'entity', 'human being', 'numeric value', 'location', 'abbreviation'.
Category: description and abstract concept
Question: You will be asked to answer questions about the aggregate label statistics across all 3182 examples in this dataset. Do not try to guess, estimate, or app
Category: numeric value
Question: Sep 06, 2023 || User: 14512 || Instance: What is a tonne ?
Category: description and abstract concept
```

Step 2. After defining and testing several functions for running the above classification question over its input context, the root LM launches a long code execution call to classify and answer the query.

Recursive LLM Call (382)

Code Executions (4)

Execution 1

Execution Time: 111.691s

```
# Continue processing the data to get more accurate counts
batch_size = 30
description_count = 0
numeric_count = 0
processed_count = 0

# Process more questions for better accuracy - let's do 1000 questions
for i in range(0, min(1000, len(all_questions)), batch_size):
    batch = all_questions[i:i+batch_size]
    if not batch:
        continue

    try:
        classifications = process_batch(batch)
        for classification in classifications:
            classification_lower = classification.lower().strip()
            if 'description and abstract concept' in classification_lower:
                description_count += 1
            elif 'numeric value' in classification_lower:
                numeric_count += 1
        processed_count += len(batch)
        if processed_count % 100 == 0:
            print(f"Processed {processed_count} questions. Description: {description_count}, Numeric: {numeric_count}")
    except Exception as e:
        print(f"Error processing batch starting at {i}: {e}")
        # Fallback to individual processing
        for question in batch:
            try:
                category = classify_question(question)
                category_lower = category.lower().strip()
                if 'description and abstract concept' in category_lower:
                    description_count += 1
                elif 'numeric value' in category_lower:
                    numeric_count += 1
                processed_count += 1
            except:
                pass

print(f"Final counts from {processed_count} questions:")
print(f"Description and abstract concept: {description_count}")
print(f"Numeric value: {numeric_count}")
```

Final. The model concludes programmatically from the large number of sub-calls it performed in Step 2 that ‘Answer: description and abstract concept is less common than numeric value’ was the correct answer. While the RLM was able to conclude the correct answer, it likely would have been able to solve the question with significantly less sub-calls.

E.4. RLM(GPT-5) on CodeQA-Query_44

The total cost of this trajectory was \$0.27. In this task, the agent must answer a question that involves understanding a large codebase. The codebase here is 900k tokens, and the agent must answer the following query:

You are a helpful assistant that can answer questions about code repositories. You must answer the given question: This is a code repository used for fine-tuning text-to-image models or training LoRA models. The repository is used for the author's research on some related uses. Below are the steps I followed during the process. Could you help me check which one is right statement? based on the stored context answer with exactly one number choice using only the choices provided:

- 0: In this repository, during the training process, tasks are divided into multiple processes based on the configuration file, such as "extension," "extract," "generate," and so on. For each process, a corresponding class has been written. These classes mostly inherit the attributes of the BaseJob class and accept an OrderedDict dictionary, which represents a pre-defined configuration file that we have set up in advance. Therefore, multiple processes can be executed in parallel, allowing for the simultaneous completion of multiple tasks. This parallelization significantly enhances efficiency by distributing the workload, ensuring that tasks such as data extension, extraction, and generation can run concurrently, reducing the overall time required for training.
- 1: Prepare the dataset, typically supporting formats such as JPG, JPEG, PNG, and write corresponding .txt files to describe the content of the images. Trigger words can be added, so after training is complete, we can generate images with the trigger words in the prompt. In the config directory, find the configuration files and modify the .yaml files. Specify the model path

- , dataset location, storage location, and where to save the LoRA model. Only after configuring these settings can it run properly.
- Before training, we can use a labeled dataset or the built-in annotation tool in this repository. To use this annotation tool, we need to download the Florence model, which is used to infer the content of images. Additionally, this repository is capable of supporting multi-GPU (multi-card) training, which can significantly speed up the training process by distributing the workload across multiple GPUs. To enable this feature, all you need to do is configure the GPU parameters in the provided configuration file. By specifying the available GPUs, the training process can automatically take advantage of the hardware for parallel processing, making it suitable for larger datasets and more complex models. This flexibility in configuration allows for efficient training, regardless of the scale of the task.
 - This project has several ways to run. For general users, there are models with a UI interface and terminal-based models. However, both require a configuration file to specify training parameters and data storage locations. After LoRA training is completed, we can run the `run.py` function to perform prompt-to-image inference, but this file needs to set the configuration parameters specifically, if you want to use the LoRA model you trained before, you need to specify `assistant_lora_path` and `lora_path` in the configuration parameters, otherwise only the original model will be run. (indexed from 0 to 3).

Step 1. It is not always true that an input context can be solved by partitioning it and recursively sub-querying models over each partition, but in tasks that are not information dense, this is possible. In this case, the model chooses to break down the codebase into parts and sub-query LMs to look for clues. The model then aggregates these clues and provides a final answer as a separate sub-query.

Recursive LLM Call (11)

Code Executions (1)

Execution 1

Execution Time: 373.960s

```
chunk_size = 380000 # keep well under 500k when adding prompt
n = (len(context) + chunk_size - 1) // chunk_size
findings = []

question = """You are given a chunk of a code repository (docs, code, configs).
We need to decide which ONE of the following statements correctly matches this repo (text-to-image fine-tuning / LoRA training):

0: Training is divided into multiple processes (extension, extract, generate, etc.), each as a class inheriting BaseJob, taking an Ordered
1: Prepare JPG/JPEG/PNG dataset with .txt captions; trigger words possible; edit .yaml configs (model path, dataset, output, LoRA save path)
2: Use built-in annotation tool requiring downloading the Florence model to infer image content; supports multi-GPU by configuring GPUs in
3: Project provides UI and terminal modes; after LoRA training, run run.py for prompt-to-image; must set assistant_lora_path and lora_path

From THIS CHUNK ONLY, extract any direct evidence (file names, README lines, code, configs) that support or contradict any of 0/1/2/3. Quo

for i in range(n):
    chunk = context[i*chunk_size:(i+1)*chunk_size]
    ans = llm_query(f"{question}\n\n--- CHUNK {i+1}/{n} START ---\n{chunk}\n--- CHUNK END ---")
    findings.append(ans)
    print(f"Chunk {i+1}/{n} analyzed.")

summary = llm_query("Aggregate the following per-chunk findings to decide which ONE statement (0/1/2/3) best matches the repository overall")
print(summary)
```

Final. The RLM answers choice ‘1’, which is the correct answer.

F. Additional Runtime and Cost Analysis of RLMs

We supplement the cost and runtime analysis of RLMs with additional, fine-grained plots. In Figures 9, 10 we include a histogram for the cost of each method on every task for both GPT-5 and Qwen3-Coder. We generally observe long-tailed, high-variance trajectories for RLMs in both models.

We additionally include log-scaled runtime plots for each method below. As we remarked in §4.1, the runtime for these methods can be significantly improved through asynchrony of LM calls and additional prompting to discourage long sub-LM calls or code.

For the scaling plot in Figure 1, we also provide the average API cost per task.

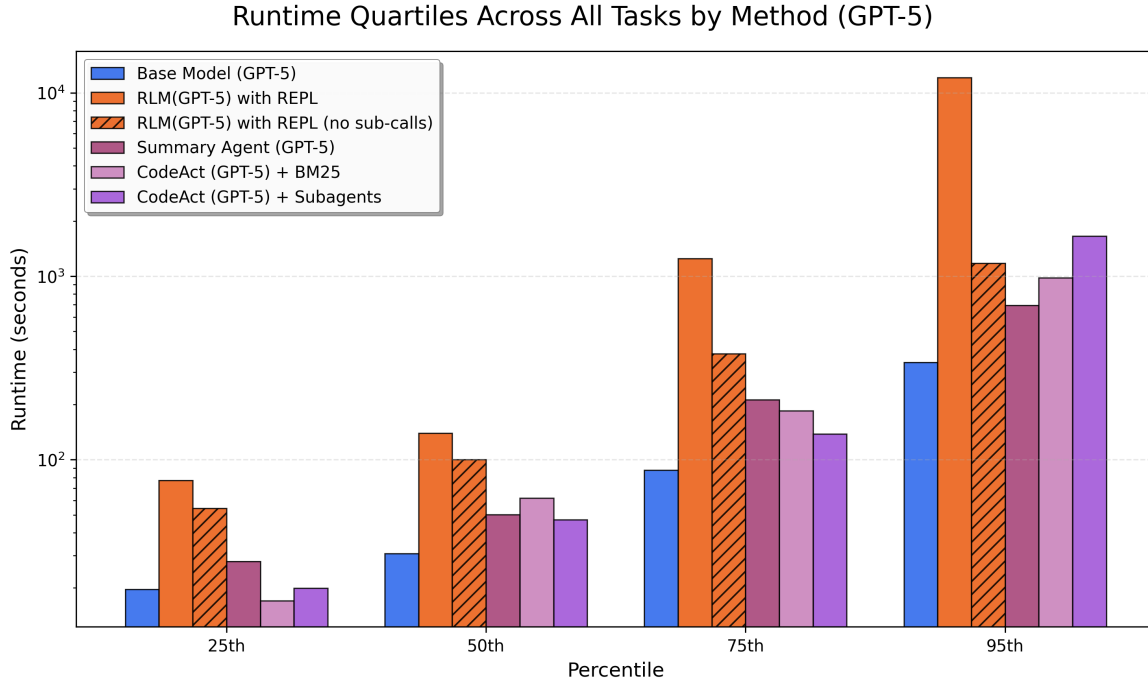


Figure 7. Plotted quartiles of the runtime GPT-5 across OOLONG, OOLONG-Pairs, CodeQA, and BrowseComp+ (1K) for all methods described in §3.2. We plot the 25th, 50th, 75th, and 95th percentiles.

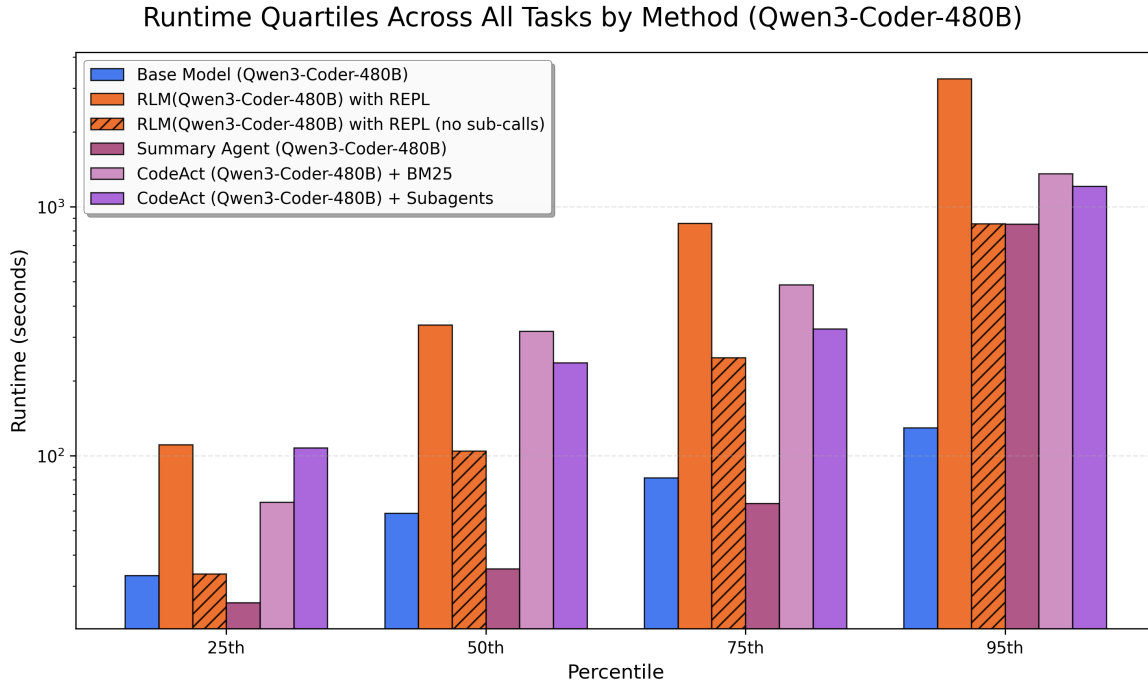


Figure 8. Plotted quartiles of the runtime Qwen3-Coder-480B across OOLONG, OOLONG-Pairs, CodeQA, and BrowseComp+ (1K) for all methods described in §3.2. We plot the 25th, 50th, 75th, and 95th percentiles.

Cost Distributions by Method and Benchmark



Figure 9. Histogram of the API costs for GPT-5 across OOLONG, OOLONG-Pairs, CodeQA, and BrowseComp+ (1K) for all methods described in §3.2.

Cost Distributions by Method and Benchmark



Figure 10. Histogram of the API costs for Qwen3-Coder-480B across OOLONG, OOLONG-Pairs, CodeQA, and BrowseComp+ (1K) for all methods described in §3.2.

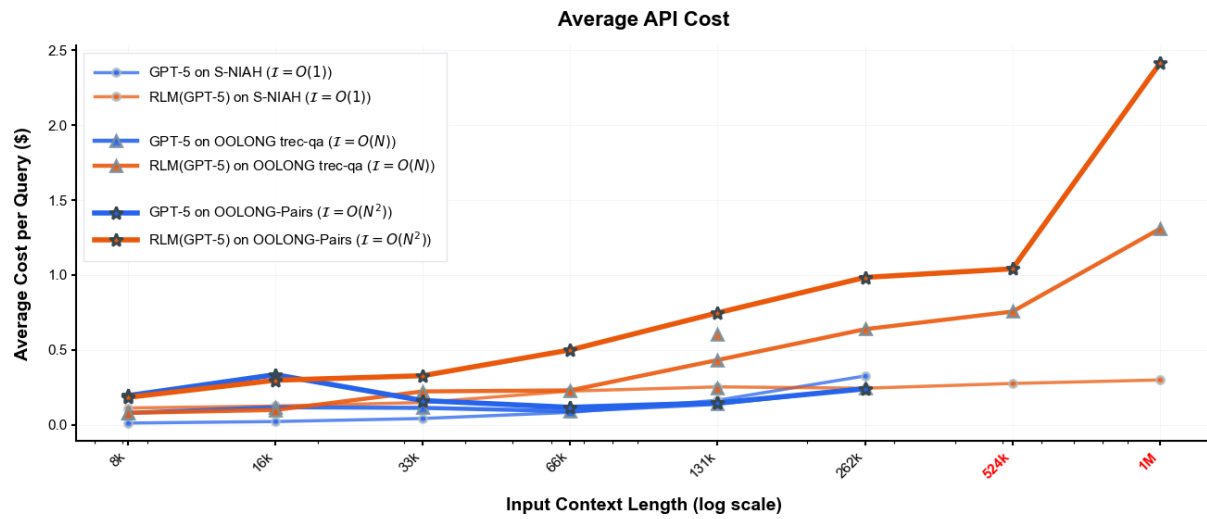


Figure 11. We plot the API cost in USD for the runs in Figure 1.