Measuring the Limits of Continual Learning for LLMs

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Abstract

Language models are trained in stages but deployed as mostly static artifacts, leaving them poorly matched to a world that continually produces novel information. This trait has motivated a broad class of *continual learning* systems that adapt models to new information through weight updates, retrieval, memory, long-context inference, or hybrid mechanisms. Yet, existing evaluations do not tell us whether such systems have truly *internalized* new information: whether they can go beyond memorizing new information and update stale beliefs, resolve indirect references, compose new facts with prior knowledge, surface facts even when only implicitly relevant, and confidently recognize gaps in its own knowledge. We construct IMPRINTBENCH, a benchmark of realistic settings that expose these systematic shortcomings. IMPRINTBENCH consists of a refreshable pipeline that automatically constructs evaluations across three domains: news events, open-source API changes, and evolving personalization histories, with queries spanning six capability families: acquisition, temporal update, referential resolution, composition, implicit relevance, and boundary awareness. Across in-the-wild update scenarios, we find common systematic failures in both retrieval-based and training-based methods, showing that current systems still fall short of robustly learning from new experience.

1. Introduction

Language models acquire their knowledge base during pretraining and post-training, and are then often deployed without further weight updates for months to service traffic. However, during deployment, relevant world information continues to evolve: APIs change, libraries deprecate functions, user preferences adapt, and world events unfold. Keeping a deployed model in sync with a constantly changing world has motivated an increasingly broad family of *continual learning* methods. These span tactics like retrieval-augmented generation (RAG), parametric updates, self-distillation, and context compression, among others.

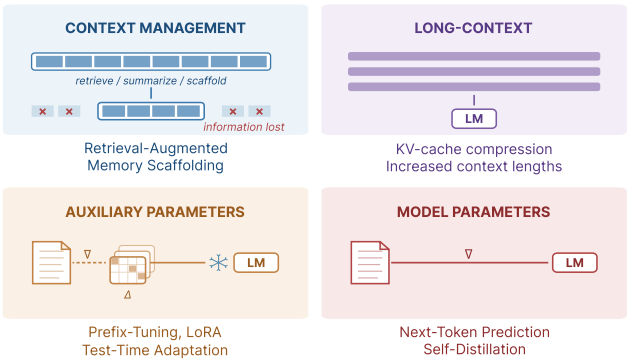

Figure 1. We study continual learning contributions from four broad families of approaches. *Context management* retrieves or summarizes corpus content into the prompt; *long-context* approaches aim to efficiently support ever-growing corpus lengths; *auxiliary parameters* compress the corpus into adapters or a KV cache that a frozen LM reads from; *model parameters* update the LM weights directly. Each family has a distinct structural limitation that becomes visible as the corpus grows.

What it actually means for a model to *internalize* this new knowledge, however, is rarely pinned down by current evaluations. Most existing evaluations only delve as deep as testing *direct recall*: after exposure to new information, e.g.. a document, news article, or API, can the model regurgitate this information when explicitly asked for it? This barometer is clearly insufficient as truly learning new information requires seamlessly integrating it into a model's internal beliefs and understanding about related areas. For example, a change in a major world political leader should not just affect an intelligent model's answer to a simple question about the identity of the current leader, but also affect its understanding of what policies that nation might be more or less likely to pursue under the new leadership. Unfortunately, current evaluations fail to test deeper understanding and might only test a single capability and domain at a time, with a single method leading to lackluster signal about which approaches work best for a range of tasks.

Existing continual learning methods occupy a handful of

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design families, and each has a structural limitation that only becomes visible as we scale the size of the corpus. A single month of world news, one popular library's accepted feature set since the last version, or a small cohort of users' interaction histories, the corpus spans hundreds of thousands to millions of tokens, and grows monotonically with time since deployment. *In-context learning* saturates the context window long before realistic update streams fit, and *retrieval-augmented* variants sidestep the context budget but inherit a coverage gap: queries with no retrievable target, such as abstaining over an unobserved fact, surfacing implicitly relevant updates, or composing across updates the query does not name, are not well-served by retrieval. Most sharply, we observe a miscalibration phenomenon where retrieving more documents helps surface relevant facts but provides no reliable signal to the model that the retrieved subset is insufficient, leading to near-total collapse on abstentions even as other metrics improve.

Memory and summarization scaffolds extend reach by compressing history into a fixed-size buffer, but the aggressive ratios required to fit large corpora degrade the same fine-grained capabilities that motivated continual learning in the first place. *Context compression* methods, such as KV-cache compression or prefix-tuning, are a promising direction; however, current state-of-the-art approaches degrade significantly at the high compression ratios required to compress large corpora. *Parametric training* is the only family that scales independently of context length and serves the full query distribution at vanilla inference cost; however, it incurs nontrivial training cost, is prone to catastrophic forgetting, and (as we show) still trails methods that simply place the corpus directly in context wherever it fits on challenging questions beyond direct recall.

In order to address this lack of signal, we introduce IMPRINTBENCH, a benchmark designed to test a wide range of continual learning capabilities. The first design commitment that distinguishes IMPRINTBENCH is breadth of measurement: every method is evaluated against a spectrum of difficult questions, and each method is given the same new knowledge corpus allowing for an apples-to-apples comparison across approaches. The second is refreshability: our evaluation questions are produced by an automatic pipeline that can be run on-demand to capture new information like world events and code library releases. This prevents contamination, and allows for longitudinal comparisons across models and methods. Our pipeline focuses on three settings meant to mirror these design principles and stress-test different continual learning methods. These settings are: *dynamic world knowledge* sourced from real news articles, *tool/library updates* drawn from popular open-source API changelogs, and *long-horizon personalization* dynamically built from streaming user histories.

We experiment with both inference-time and training-time methods with matched exposure budgets. We find that direct recall is a poor predictor of performance on other tasks of interest. We also observe interesting failure cases for each continual learning mechanism. For example, retrieval-based methods recover surface facts well, but fail to index them into prior knowledge hierarchies. Meanwhile, training-based methods can confidentally assert negative existence queries, but some struggle with temporal updates. No method we evaluate is robust across the full set of capabilities. This suggests that each continual learning system may optimize along certain axes of capability.

Concretely, our contributions are:

- A capability decomposition of internalization grounded in documented failure modes.
- IMPRINTBENCH, an auto-refreshing benchmark and pipeline to test the above capabilities.
- A unified evaluation of several inference-time and training-time continual learning methods in controlled compute- and data-matched conditions.
- Analysis of where and how current continual learning methods fail, and their overhead costs.

2. Beyond Recall: Measuring *Internalization*

A benchmark for continual learning should ask not only whether a model can recall newly exposed information, but whether that information changes what the model can correctly do afterward. We identify six central capabilities to test for internalization of knowledge updates.

Direct and Indirect Recall. The floor is *direct acquisition* (**DirAcq**): the model should confirm a newly exposed fact when asked about it directly. A step above memorization, *reference resolution* (**RefRes**) queries the same fact through aliases, paraphrases, descriptions, or role-based identifiers. *Implicit relevance* (**ImpRel**) tests whether the model has indexed new facts under high-level characteristics: when they happened, what topic they cover, how salient they were. E.g., "what happened around the world this week?" after exposure to that week's news articles.

Reasoning over Updates. *Temporal update* (**TempUpd**) questions test whether the model recognizes that a new fact supersedes an older one rather than answering with the stale state. *Compositional reasoning* (**CompRel**) tests whether the model can reason *with* the update: combining it across multiple exposed facts or with prior knowledge.

Knowing When Not to Answer. *Boundary awareness* (**BoundAbs**) is the complement of the preceding capabilities: rather than asking what the model has internalized, it

tests whether the model abstains when no exposed evidence justifies a confident answer. Update-heavy settings routinely contain partial or absent information, and many queries are correctly answered only by acknowledging that the system does not yet know enough.

We construct our benchmark around three realistic settings: dynamic world knowledge (World News), tool/library updates (Code Changelogs), and evolving user states (Personalization). Each setting is accompanied by a refreshable pipeline that automatically scrapes or generates a corpus and evaluation questions to test each capability above. We include further details on each pipeline's scraping, filtering, and validation logic in Section D, with supplementary statistics in Section B.

World News. We mine major world events from spikes in high-volume prediction markets on Polymarket, search for relevant news articles around around their timestamp, and ground the entities into a relationship graph from crawling Wikipedia.

Code Changelogs. We extract function signature updates from the changelogs of five major open-source Python libraries (`numpy`, `pandas`, `polars`, `pytorch`, and `scipy`) on GitHub, search for real-world usages of them using GitHub code search, and extract minimal snippets of the update.

Personalization. We transform long-horizon personalization data (Jiang et al., 2025; Li et al., 2026) into streaming user-state updates, where dialogues contain and update facts about a user's preferences and life events, and use a ledger to test whether methods maintain and apply an evolving user model.

World News	
DirAcq	Did an Israeli airstrike kill Iran's late Supreme Leader Ayatollah Khamenei in early March 2026?
TempUpd	As of 2026-03-12, who holds the role of Supreme Leader of Iran?
CompRel	Was the current Supreme Leader of Iran born after the end of World War II?
ImpRel	What major geopolitical events happened in early March 2026 in the Middle East?
BoundAbs	Did the UN Security Council adopt Resolution 2715 in late February 2026 demanding a ceasefire?
Code Changelogs	
DirAcq	Does NumPy have a function at `numpy.strings.slice`?
RefRes	What function in NumPy extracts substrings from an array of strings using start, stop, and . . . ?
CompRel	Which function fits in the masked snippet below to extract a substring of specific . . . ?
ImpRel	What functions are in `numpy.strings`?
Personalization	
RefRes	*(after the user mentioned solving crosswords and logic puzzles in passing)* What sort of brain-teasing pastime does the user enjoy in their spare time?
TempUpd	*(after the user expressed enthusiasm for African history documentaries earlier and later said they were tired of the genre)* Which documentary gift option should be avoided when narrowing down the shortlist?
CompRel	*(after the user said they enjoy action-adventure games and prefer VR over flat-screen play)* Which game suits this user best — VR action-adventure, non-VR action-adventure, VR puzzle, or non-VR puzzle?
ImpRel	*(after the user mentioned a low tolerance for strong spice)* Which dinner spot should be suggested: a gently seasoned Mediterranean bistro or a chili-forward Sichuan restaurant?
BoundAbs	*(the user has never said anything about gardening)* What kind of gardening setup do I keep at home?

Figure 2. **Selected test queries.** Each row is a representative item generated by our pipeline for a given settin and question type. Each setting emphasizes a different subset of the question types based on the structure of its updates. We provide detailed statistics of each setting in Section B.

3. Experimental Methodology

Our experimental design addresses two blind spots in prior continual-learning evaluations.

1. First, we compute- and data-match every parametric baseline against an interleaved supervision over both the raw corpus and the synthetic QA pairs. Recent works on self-distillation (Shenfeld et al., 2026; Zhao et al., 2026; Ye et al., 2026) use the QA pairs only as a self-study signal alongside the corpus and do not run this joint configuration directly.

2. Second, we sweep effective compression ratios for both in-context and parametric methods to isolate how each method's accuracy scales with corpus size. As real-world update corpora are massive, the increased compression as this scales surfaces the poor scaling behavior of summarization and memory methods.

Training data. Across all methods, we vary the supervision source: the raw update corpus (C), the synthetic QA pairs (Q), or both interleaved (C+Q). Table 10 defines C and Q per setting.

Models. We run our main evaluations on Qwen3-30B-A3B-Instruct-2507 and targeted ablations on Qwen3-4B-Instruct-2507. All three are instruct-tuned and support native context windows long enough to host the in-context baselines below.

3.1. Baselines

We briefly describe each baseline below and report detailed hyperparameters in Section C.

Retrieval. We evaluate three retrieval-augmented generation variants spanning a spectrum of retrieval fidelity. Oracle prepends the exact context used to generate each query, providing an upper bound against which the other variants can be calibrated. Hybrid retrieves k closest de-duplicated documents by cosine similarity into the prompt. Agentic equips the model with a retrieval tool that invokes the same hybrid retriever up to k times. We sweep $k \in \{3, 5, 10\}$ for both Hybrid and Agentic RAG to characterize the relationship between per-step retrieval budget and answer quality.

Summarization. Since the entire corpus in each of our settings exceeds standard context windows, we use a fixed chunk-size of 32768 tokens and prompt the model to summarize into {512, 1024, 2048} tokens to simulate a 64×, 32×, and 16× compression ratio along the token dimension. In practice, the compression ratio is variable and we report it in Tables 1–3. As a finer-grained alternative, we also produce one summary per document (per-feature on Code Changelogs, per-article on World News) — see Table 13.

Memory Scaffolding. We implement a core-memory-only variant of MemGPT (Packer et al., 2024). An LLM processes update chunks sequentially and rewrites a setting-specific structured memory under a fixed token budget, with sections for active, superseded, and uncertain facts. We evaluate two compression levels, $32\times$ and $64\times$ smaller than the original corpus. At test time, the model answers using only this structured memory.

Context Compression. We study three distinct mechanisms of context compression: textual summarization via prompting, KV-cache compression, and prefix-tuning. We select KVzip (Kim et al., 2025) and Cartridges (Eyuboglu et al., 2025) as our latter two methods. To scale beyond the context window, we follow each method's original recipe: KVzip uses its default fixed chunk size of 2048 tokens, and Cartridges is trained on the corpus chunked into its constituent documents. We use a compression ratio of 16× for KVzip. For Cartridges, we train a fixed 4096 token prefix, yielding a different compression ratio for each corpus.

Parametric Training. We evaluate three parametric training objectives: next-token prediction on the exposed corpus (C), supervised fine-tuning on generated question-answer pairs (Q), and self-distillation (Shenfeld et al., 2026). For the first two objectives, we consider full-parameter fine-tuning and low-rank adaptation (LoRA). To provide a matched baseline for self-distillation, we also train a C+Q variant that combines next-token prediction on the corpus with supervised fine-tuning on the generated questions. Following (Shenfeld et al., 2026), we train with dense per-token supervision from the same model with privileged information dependent on the setting. We train the student on its answer tokens by minimizing reverse KL to the teacher's next-token logits at each position. On Code Changelogs we additionally compare against finer-grained LoRA adapters (one per library) in Table 13.

Additional implementation details for all methods are provided in Section C.2.

4. Results & Analysis

Full per-method, per-question-type Pass@1/AllCorrect@8 numbers across all three settings on Qwen3-30B-A3B-Instruct-2507 are reported in Tables 1, 2, and 3. We include a smaller-base ablation for Qwen3-4B-Instruct-2507 in Table 4.

Context management scales poorly with corpus size. Figure 3 plots Pass@1 against the effective number of in-context tokens per query. Across all three settings, in-context methods lose 20–40 points of Pass@1 as the budget tightens from ∼15× to ∼80× compression. Parametric methods (SFT, SDFT) place no corpus tokens in context and hold flat as the corpus grows, but trail the high-budget operating points of in-context methods on World News and Code Changelogs.

Retrieval struggles with certain question types. As shown in Figure 4, increasing the retrieval budget does not lead to improved performance on most question types. In particular, we find that BoundAbs, which requires an exhaustive set of articles to confidently deny the existence of a fictitious fact, has almost zero success in all retrieval budgets. Surprisingly, the largest gains instead appear on ImpRel.

SFT can match SDFT in data-matched settings. Under matched C+Q supervision (Figure 5), SFT and SDFT track within a few points on most question types in World News and Code Changelogs, and SDFT is actually 26 points *worse* than SFT on World News DirAcq. The exception is small-corpus Personalization, where SDFT keeps a ∼5–15-point edge.

SFT excels at new-fact assertion; SDFT excels at old-fact preservation. Splitting World News TempUpd into four temporal axes (Figure 6) reveals a clear trade-off: SFT wins where the model must commit to the new entity (forward, backward), while SDFT wins where it must operate on the old entity (negation, prior identity).

Context compression methods degrade severely compared to compute-matched alternatives. We compare KV-cache compression (KVzip, Figure 7) and auxiliary-parameter compression (Cartridges, Figure 8) against

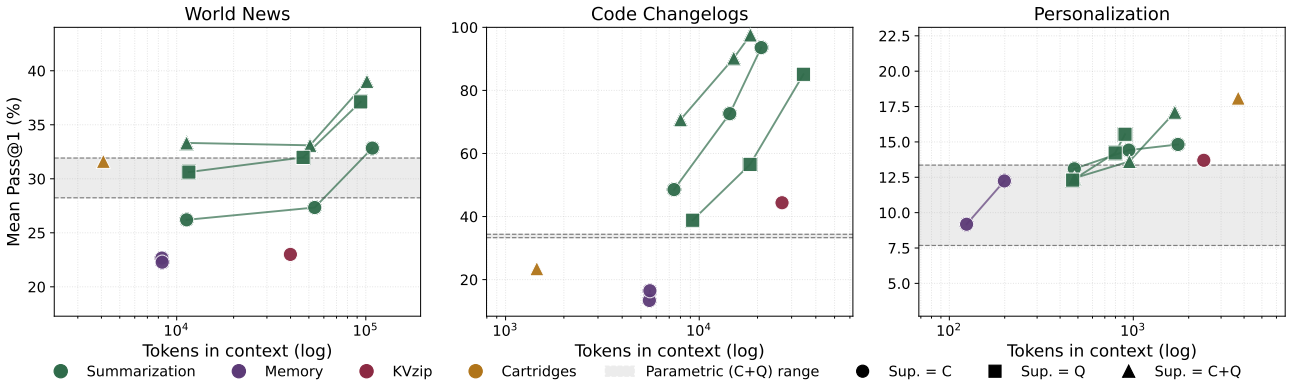

Figure 3. **Context management scales poorly.** Higher compression (moving left) simulates the regime where corpora no longer fit in context; Pass@1 falls sharply as the in-context budget shrinks. Gray band: SFT/SDFT (C+Q) Pass@1 range.

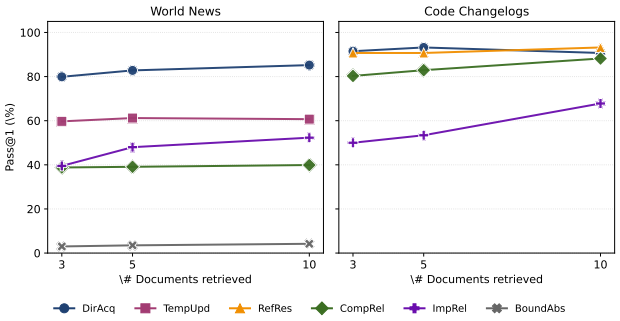

Figure 4. **Change in Pass@1 vs. retrieval depth, per question type and setting.** Increasing retrieved documents from 3 to 10 primarily improves ImpRel, while BoundAbs continues to struggle and DirAcq remains comparatively flat. Gains are reported relative to the 3-document baseline.

Figure 5. **SFT (C+Q) vs SDFT (C+Q) per question type.** Solid: Pass@1; dashed: AllCorrect@8. Error bars are ±1 SE on World News and Code Changelogs.

compute-matched baselines that share the same supervision and a comparable token budget: Chunked Summary 32K→1K (C) for KVzip (∼16×), full-parameter SFT (C+Q) for Cartridges on World News/Code Changelogs (fixed 4096-token prefix), and Chunked Summary 32K→2K (C+Q) for Cartridges on Personalization (where the per-persona cartridge is only ∼10×).

Backbone matters. Swapping Qwen3-30B-A3B-Instruct-2507 for the smaller Qwen3-4B-Instruct-2507 produces a modest drop on World News across most methods (Figure 9).

5. Discussion

We introduced IMPRINTBENCH, an evaluation suite for continual learning across three real-world update regimes (world news, code APIs, and personalized assistants) with six question families that probe how a model treats new information beyond rote recall. Across all three settings, no current method internalizes updates cleanly. Retrieval-based methods fail to scale for negative existence queries, context management approaches (such as summarization and memory) lose 20–40 points of Pass@1 at realistic compression ratios, and context compression methods (KVzip, Cartridges) underperform compute-matched baselines. Parametric methods (SFT, SDFT) trail in-context methods at the largest token budgets but become competitive only as compression tightens. Within parametric methods, plain SFT matches self-distillation given matched training data, though the two diverge along temporal axes: SFT commits to the new entity, while SDFT preserves the old. We hope IMPRINTBENCH serves as a stress test for the next generation of update-time learning systems.

Limitations. Our corpora exceed a typical context window but not by orders of magnitude: we do not stress months- or years-long accumulation regimes where in-context families would be further disadvantaged and parametric or hybrid approaches may begin to dominate outright. We see this as a natural extension for future work.

6. Related Work

Continual Learning. Large language models (LLMs) are pretrained once on static internet-scale corpora (Brown et al., 2020; Grattafiori et al., 2024), before being adapted for downstream tasks via several stages of post-training,

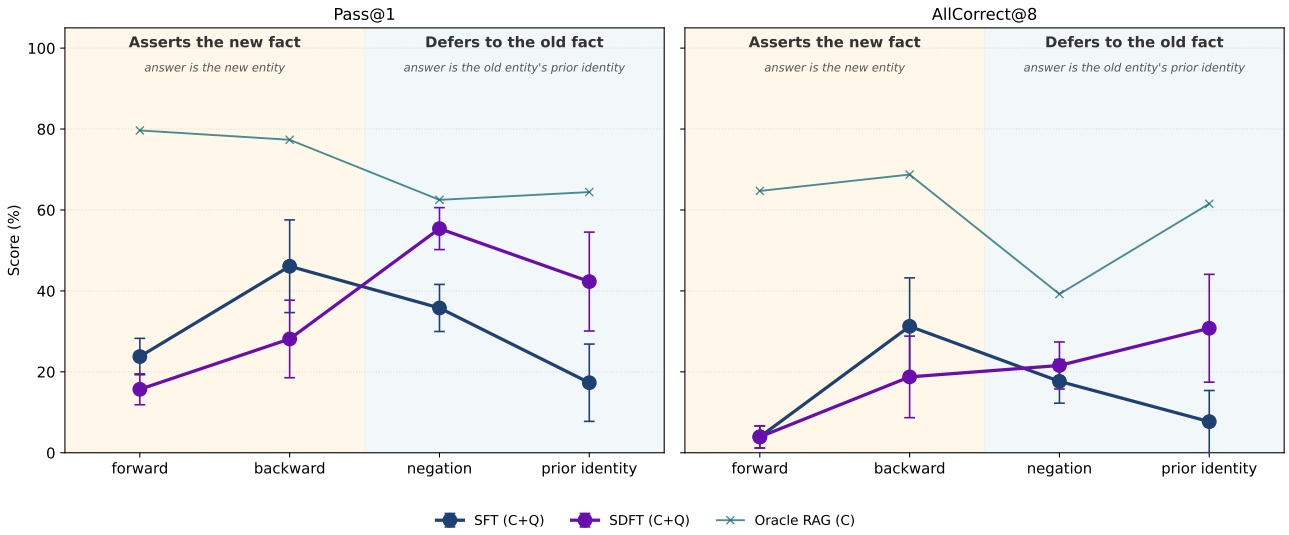

Figure 6. **World News TempUpd split into four temporal axes.** *Forward*: "who holds role X?" answer is the new entity. *Backward*: "what role does the old entity hold?" answer is the new role. *Negation*: "does the old entity still hold X?" answer is no. *Prior identity*: "what role did the old entity hold before?" Forward and backward axes assert the new fact; negation and prior-identity axes defer to the old fact. Vanilla RAG (top-10) is a thin in-context reference. Left: Pass@1; right: AllCorrect@8.

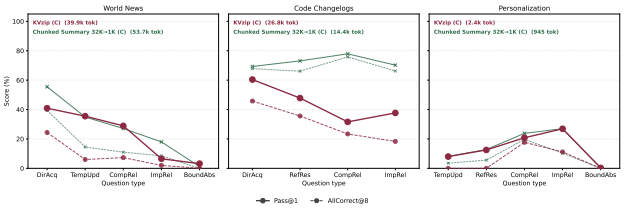

Figure 7. **KVzip underperforms Chunked Summarization at a higher token-budget.** To compute-matched, we use a 32× chunked summarization against a ∼16× KVzip compression.

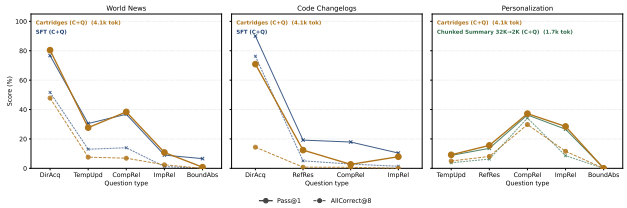

Figure 8. **Cartridges underperforms full-parameter SFT (C+Q).** Cartridges' fixed 4096-token prefix is compute-matched to SFT zero-budget on the larger settings. On Personalization, where the per-persona cartridge is only ∼10× compression, we use a more aggressive 16× summary baseline that still wins.

preference calibration, and safety tuning. However, they are deployed in a changing world that contains frequent knowledge updates, experience, and changes in values and preference priors. The computational cost of pretraining, estimated at tens of millions of GPU-hours for large models (Grattafiori et al., 2024), makes retraining from scratch infeasible at any practical frequency.

While adapting a pretrained model via supervised fine-tuning (SFT) on new data is a possible solution, standard SFT suffers from severe catastrophic forgetting since the performance on previously learned tasks degrades as the model's parameters are updated using the SFT data (Kalajdzievski, 2024). Parameter-efficient methods such as LoRA (Hu et al., 2021) can mitigate catastrophic forgetting by constraining parameter updates to a low-rank subspace, but as Biderman et al. (2024) demonstrate, this comes at the expense of reduced learning capacity.

Shenfeld et al. (2026) show that self-distillation from a frozen copy of the model enables continual learning with substantially less forgetting than standard SFT, while retaining the expressivity of full-rank updates. However, the Knowledge Update Playground (KUP) benchmark shows that even the best continual learning methods still struggle to simultaneously internalize new facts and reason compositionally over them (Li & Goyal, 2025).

In-context Learning. An alternative to parametric updates is to provide new information directly in the model's context at inference time. Brown et al. (2020) demonstrate that large language models are effective few-shot learners, capable of adapting to novel tasks from a handful of input-output demonstrations without any gradient updates. Retrieval-augmented generation (RAG) extends this concept by dynamically retrieving relevant documents and prepending them to the prompt (Lewis et al., 2020; Gao et al., 2024). However, this non-parametric approach faces significant scaling limitations. Liu et al. (2024) show that models strug-

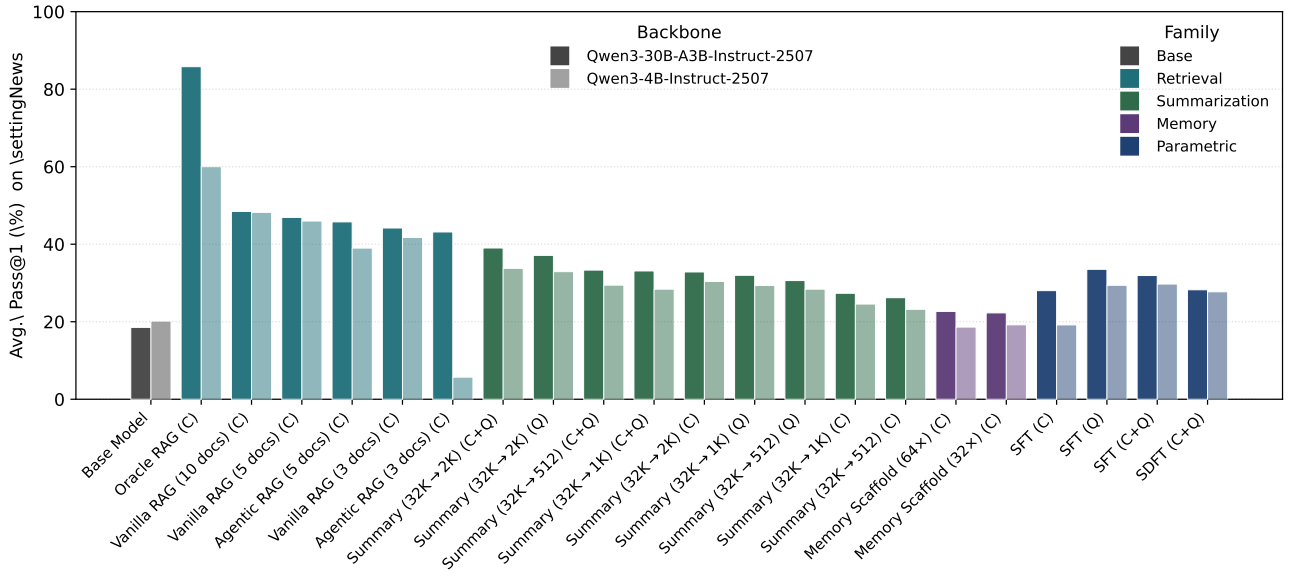

Figure 9. **Backbone comparison on World News.** Qwen3-30B-A3B-Instruct-2507 (solid) vs Qwen3-4B-Instruct-2507 (faded), per method (averaged across question types). The smaller backbone trails on most methods, with the largest gaps on Agentic RAG and parametric SFT/SDFT.

gle to effectively use information positioned in the middle of long contexts, and Li et al. (2024) demonstrate that even state-of-the-art long-context LLMs degrade substantially as the number of in-context examples grows into the hundreds.

More recently, Dou et al. (2026) introduced CL-Bench, a real-world benchmark that includes 500 complex contexts crafted by domain experts, confirming that even if new architectures could resolve the positional degradation problem highlighted by (Liu et al., 2024), in-context learning alone remains insufficient for internalizing large amounts of new knowledge into the model.

Context Management & Memory. A growing body of work attempts to bridge purely non-parametric retrieval and fully parametric updates by equipping language models with explicit memory. Non-parametric approaches include storing long-term memory entries that are cached and retrieved as needed. (Chen et al., 2026; Wu et al., 2024; Maharana et al., 2024) effectively extending the model's accessible context without modifying its weights. On the parametric side, Wang et al. (2024) propose MemoryLLM, which incorporates a self-updatable memory pool directly into the model's latent space, enabling the model to absorb new information through forward passes alone. Das et al. (2024) take an alternative approach with Larimar, using an external episodic memory controller inspired by the learning systems in the brain to perform fast, one-shot knowledge edits without retraining. Tack et al. (2024) propose online adaptation through amortized context representations that are stored and retrieved as needed, combining the efficiency of retrieval with the expressivity of learned representations. While these memory-augmented approaches resolve some of the context-length constraints, they remain limited in their capacity for deep knowledge integration and compositional reasoning over newly acquired information.

Test-Time Training. Test-time training (TTT) offers a principled approach to adapting the model on the fly. Sun et al. (2024) introduce TTT layers that replace the fixed hidden state of recurrent models with a learnable model updated via self-supervised gradient descent at inference time, demonstrating promising scaling laws with context length. Tandon et al. (2025) extend this idea for long-context test-time scaling, training the model via meta-learning to learn how to learn at test time, achieving strong performance on long-context benchmarks. While promising, existing TTT approaches have primarily been evaluated on single-document comprehension tasks and rely on general-purpose self-supervised objectives; they have not been designed for the corpora-level knowledge update and multi-hop reasoning need for effectve continual learning.

KV Cache Compression. A complementary line of work compresses the key-value (KV) cache representations that encode context into more compact forms. Kim et al. (2025) propose KVzip, a query-agnostic compression method that reconstructs the essential context from a small subset of KV pairs, reducing the memory footprint during inference while maintaining the generation quality. Charakorn et al. (2026) introduce Doc-to-LoRA, which distills an entire document's information into a set of LoRA parameters, allowing for

context internalization without needing the document to be in the prompt at inference time. Similarly, Eyuboglu et al. (2025) propose Cartridges, lightweight adapter modules trained via self-study to capture long-context information into reusable representations. These methods are at the intersection of context compression and parametric learning, but are typically trained on single documents rather than evolving corpora, and do not address the challenges of sequential knowledge accumulation over time.

Impact Statement

This paper presents work whose goal is to advance the field of Machine Learning. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

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Method	Sup.	Compr.	DirAcq	TempUpd	RefRes	CompRel	ImpRel	BoundAbs	Avg.
Base Model		–	30.9 15.6	30.3 12.2	–	24.7 9.9	0.0 0.0	6.8 0.0	18.5 7.5
Oracle RAG	C	–	85.6 73.9	80.2 58.8	–	71.7 58.2	91.5 65.9	–	–
Vanilla RAG (3 docs)	C	54.4×	79.9 71.1	59.7 39.7	–	38.8 18.6	39.5 26.8	3.0 0.0	44.2 31.3
Vanilla RAG (5 docs)	C	32.5×	82.8 72.2	61.2 39.7	–	39.1 22.7	48.0 28.0	3.5 0.0	46.9 32.5
Vanilla RAG (10 docs)	C	16.5×	85.2 72.2	60.7 38.9	–	39.9 23.2	52.3 37.8	4.2 0.0	48.5 34.4
Agentic RAG (3 docs)	C	226.8×	69.8 48.3	62.2 42.7	–	38.1 13.8	42.7 25.6	3.0 0.0	43.2 26.1
Agentic RAG (5 docs)	C	135.9×	76.5 53.9	62.8 41.2	–	36.5 15.1	48.8 23.2	4.2 0.0	45.8 26.7
Agentic RAG (10 docs)	C	67.9×	78.1 56.7	62.8 36.6	–	34.1 11.7	52.7 28.0	4.4 0.0	46.4 26.6
Memory Scaffold (32×)	C	76.2×	43.9 30.0	28.5 12.2	–	26.2 11.0	12.3 3.7	0.5 0.0	22.3 11.4
Memory Scaffold (64×)	C	76.5×	47.1 32.2	28.8 9.2	–	25.3 8.7	11.9 7.3	0.2 0.0	22.6 11.5
KVzip	C	16×	40.9 24.4	35.5 6.0	–	28.9 7.3	6.5 2.0	3.2 0.0	23.0 8.0
Cartridges	C+Q	156.0×	80.4 47.8	27.7 7.6	–	38.4 6.9	10.8 2.4	0.8 0.0	31.6 13.0
Chunked Summary (32K→2K)	C	5.9×	63.7 48.3	42.9 17.6	–	28.2 8.2	28.8 12.2	0.6 0.0	32.9 17.2
Chunked Summary (32K→1K)	C	11.9×	55.5 39.4	34.9 14.5	–	27.1 11.0	18.0 8.5	1.2 0.0	27.3 14.7
Chunked Summary (32K→512)	C	56.6×	50.1 37.2	32.1 15.3	–	29.2 13.5	19.1 14.6	0.5 0.0	26.2 16.1
SFT	C	–	73.8 50.6	24.6 8.4	–	35.2 9.2	4.7 0.0	1.8 0.0	28.0 13.6
+ LoRA	C	–	44.4 35.0	30.5 16.8	–	31.8 14.3	0.5 0.0	0.2 0.0	21.5 13.2
Chunked Summary (32K→2K)	Q	6.8×	69.5 52.8	45.3 21.4	–	35.6 13.3	32.9 22.0	2.3 0.0	37.1 21.9
Chunked Summary (32K→1K)	Q	13.7×	56.7 41.7	42.1 19.1	–	33.5 11.7	26.4 17.1	1.2 0.0	32.0 17.9
Chunked Summary (32K→512)	Q	55.1×	47.6 33.9	43.2 26.7	–	33.3 14.0	26.7 18.3	2.3 0.0	30.6 18.6
SFT	Q	–	82.5 57.8	33.5 14.5	–	39.3 17.6	7.2 0.0	5.1 0.0	33.5 18.0
+ LoRA	Q	–	75.9 38.3	33.9 15.3	–	39.6 9.4	5.6 0.0	3.0 0.0	31.6 12.6
Chunked Summary (32K→2K)	C+Q	6.3×	72.4 53.3	46.8 24.4	–	32.8 10.5	40.5 25.6	2.6 0.0	39.0 22.8
Chunked Summary (32K→1K)	C+Q	12.6×	65.5 47.2	39.6 16.0	–	31.0 9.2	27.9 19.5	1.5 0.0	33.1 18.4
Chunked Summary (32K→512)	C+Q	56.6×	63.1 48.9	40.3 18.3	–	32.2 13.8	29.6 22.0	1.4 0.0	33.3 20.6
SFT	C+Q	–	76.7 51.7	30.5 13.0	–	36.8 14.0	9.0 1.2	6.6 0.0	31.9 16.0
+ LoRA	C+Q	–	73.8 36.1	30.0 11.5	–	41.1 11.0	7.8 0.0	4.7 0.0	31.4 11.7
SDFT	C+Q	–	51.3 32.2	35.3 15.3	–	32.9 6.9	15.4 2.4	6.3 0.0	28.3 11.4

Table 1. **World News results on Qwen3-30B-A3B-Instruct-2507.** Pass@1 / AllCorrect@8 per question type. **Sup.**: C=raw corpus, Q=synthetic QA pairs, C+Q=both interleaved; see Table 10. **Compr.** is the effective compression ratio. For each (method, supervision) we report the hyperparameter with the highest average score (excluding DirAcq).

A. Full Results Tables

We report all main results for Qwen3-30B-A3B-Instruct-2507 below, split by setting. We re-run the World News pipeline with Qwen3-4B-Instruct-2507 as the base model and parametric finetune target (Table 4).

B. Benchmark Statistics

B.1. Corpus Statistics

Table 5 summarizes the corpus statistics for both settings. All token counts are computed with the Qwen3-30B-A3B-Instruct-2507 tokenizer. For Code Changelogs, "Article" refers to the human-readable documentation aggregated for an accepted feature (release-note bullet, full docs page, PR metadata, summary), excluding the raw patches and diffs that are still appended during NTP training. For World News, "Article" is the cleaned news-article body (`article.txt`).

B.2. World News: by month

Table 6 breaks the World News corpus down by month of publication.

B.3. Code Changelogs: by library

Table 7 breaks the Code Changelogs corpus down by library.

B.4. Evaluation Statistics

Table 9 reports the number of evaluation questions per question type for each setting, along with the mean number of corpus tokens needed to answer each question (sum of tokens across all articles the question depends on, averaged within question type). ImpRel questions reference cluster-level information rather than a single article and are reported with a dash;

Method	Sup.	Compr.	DirAcq	TempUpd	RefRes	CompRel	ImpRel	BoundAbs	Avg.
Base Model		–	7.8 5.1	–	12.2 5.1	1.4 0.5	7.2 0.0	–	7.2 2.7
Oracle RAG	C	245.2×	98.3 96.0	–	90.5 72.0	99.6 99.3	99.8 98.6	–	97.0 91.5
Vanilla RAG (3 docs)	C	54.4×	91.5 92.4	–	90.7 82.2	80.3 78.9	50.0 35.2	–	78.1 72.2
Vanilla RAG (5 docs)	C	32.5×	93.2 93.2	–	90.7 82.2	82.9 80.3	53.4 38.0	–	80.1 73.4
Vanilla RAG (10 docs)	C	16.5×	90.7 89.8	–	93.2 85.6	88.2 85.6	67.8 64.8	–	85.0 81.5
Memory Scaffold (32×)	C	77.5×	13.5 5.9	–	7.8 0.0	28.6 25.1	3.7 0.0	–	13.4 7.8
Memory Scaffold (64×)	C	77.0×	15.3 1.7	–	11.9 0.0	36.8 33.7	1.9 0.0	–	16.5 8.9
KVzip	C	16×	60.4 45.8	–	47.8 35.6	31.6 23.4	37.7 18.3	–	44.4 30.8
Cartridges	C+Q	295.4×	70.9 14.4	–	12.4 0.8	2.7 0.7	7.9 0.0	–	23.5 4.0
Chunked Summary (32K→2K)	C	20.5×	95.8 95.8	–	95.7 93.2	95.8 94.7	87.0 77.5	–	93.5 90.3
Chunked Summary (32K→1K)	C	29.8×	69.3 67.8	–	73.1 66.1	77.9 75.8	70.2 66.2	–	72.6 69.0
Chunked Summary (32K→512)	C	57.8×	43.4 42.4	–	57.1 50.0	45.8 44.0	47.9 45.1	–	48.5 45.4
SFT	C	–	19.0 5.1	–	33.0 13.6	16.5 6.0	6.5 0.0	–	18.8 6.2
+ LoRA	C	–	7.6 5.9	–	34.4 20.3	1.4 0.0	11.6 5.6	–	13.8 8.0
Chunked Summary (32K→2K)	Q	12.4×	88.3 87.3	–	88.9 83.9	79.2 76.8	84.0 62.0	–	85.1 77.5
Chunked Summary (32K→1K)	Q	23.4×	58.7 58.5	–	44.1 10.2	60.3 52.4	63.0 57.7	–	56.5 44.7
Chunked Summary (32K→512)	Q	46.3×	37.0 31.4	–	32.5 11.0	42.7 25.8	43.1 33.8	–	38.8 25.5
SFT	Q	–	95.4 84.7	–	14.5 5.1	20.8 9.3	8.8 1.4	–	34.9 25.1
+ LoRA	Q	–	80.6 44.1	–	20.7 5.9	9.7 3.1	6.3 0.0	–	29.3 13.3
Chunked Summary (32K→2K)	C+Q	23.3×	100.0 100.0	–	98.0 94.9	96.6 95.0	95.8 84.5	–	97.6 93.6
Chunked Summary (32K→1K)	C+Q	28.4×	92.4 92.4	–	91.8 89.0	90.9 89.7	85.9 69.0	–	90.3 85.0
Chunked Summary (32K→512)	C+Q	53.5×	72.0 72.0	–	76.4 72.9	61.8 59.8	72.7 60.6	–	70.7 66.3
SFT	C+Q	–	90.0 76.3	–	19.2 5.1	17.9 2.9	10.4 1.4	–	34.4 21.4
+ LoRA	C+Q	–	79.7 39.8	–	20.1 5.9	10.9 2.4	7.2 1.4	–	29.5 12.4
SDFT	C+Q	–	94.0 87.3	–	18.9 5.1	9.9 2.4	10.4 0.0	–	33.3 23.7

Table 2. **Code Changelogs results on Qwen3-30B-A3B-Instruct-2507.** Pass@1 / AllCorrect@8 per question type. **Sup.**: C=raw corpus, Q=synthetic QA pairs, C+Q=both interleaved; see Table 10. **Compr.** is the effective compression ratio. For each (method, supervision) we report the hyperparameter with the highest average score (excluding DirAcq).

Method	Sup.	Compr.	DirAcq	TempUpd	RefRes	CompRel	ImpRel	BoundAbs	Avg.
Base Model		–	–	1.2 –	4.0 –	17.1 –	13.8 –	0.0 0.0	16.3 –
Oracle RAG	C	–	–	18.9 –	34.1 –	44.7 –	41.4 –	23.1 –	32.4 –
Vanilla RAG (10 docs)	C	–	–	21.5 7.1	27.0 7.9	27.6 17.1	32.8 10.3	22.3 0.0	23.5 6.8
Agentic RAG (10 docs)	C	–	–	8.7 –	19.8 –	27.6 –	19.8 –	6.7 –	11.4 –
Memory Scaffold (32×)	C	194.2×	–	5.7 3.0	13.3 10.3	18.3 17.1	21.2 6.0	2.7 0.0	12.2 7.3
Memory Scaffold (64×)	C	311.5×	–	3.2 1.6	4.9 3.2	15.8 13.2	19.3 4.3	2.7 0.0	9.2 4.4
KVzip	C	16×	–	8.0 0.0	12.5 0.0	20.8 17.7	26.9 11.2	0.3 0.0	17.0 10.4
Cartridges	C+Q	10.4×	–	9.2 5.0	15.6 8.1	37.2 29.8	28.5 11.6	0.0 0.0	15.1 9.1
Chunked Summary (32K→2K)	C	22.1×	–	9.6 4.0	14.8 5.6	22.0 19.7	27.7 12.1	0.0 0.0	14.8 8.3
Chunked Summary (32K→1K)	C	40.9×	–	8.1 3.5	12.8 5.6	23.8 19.7	27.0 10.3	0.4 0.0	14.4 7.8
Chunked Summary (32K→512)	C	80.9×	–	6.1 2.3	7.4 4.8	23.4 17.1	27.9 11.2	0.7 0.0	13.1 7.1
SFT	C	–	–	1.0 0.0	3.0 0.0	19.7 2.6	12.9 1.7	0.0 0.0	10.3 0.9
+ LoRA	C	–	–	1.1 0.1	3.4 0.0	20.1 10.5	13.1 4.3	0.0 0.0	7.5 3.0
Chunked Summary (32K→2K)	Q	42.9×	–	10.5 6.6	17.5 14.3	21.2 18.4	28.0 11.2	0.5 0.0	15.5 10.1
Chunked Summary (32K→1K)	Q	48.5×	–	9.3 5.2	14.5 10.3	26.0 22.4	20.7 7.8	0.6 0.0	14.2 9.1
Chunked Summary (32K→512)	Q	82.6×	–	6.0 3.2	8.2 5.6	24.2 22.4	21.9 7.8	1.2 0.0	12.3 7.8
SFT	Q	–	–	2.8 0.0	9.2 0.8	21.7 7.9	15.2 1.7	0.0 0.0	11.4 2.1
+ LoRA	Q	–	–	3.5 0.3	10.6 0.8	26.5 13.2	10.9 1.7	0.0 0.0	10.3 3.2
Chunked Summary (32K→2K)	C+Q	23.0×	–	8.8 3.8	13.6 6.3	36.3 34.2	26.6 8.6	0.2 0.0	17.1 10.6
Chunked Summary (32K→1K)	C+Q	40.6×	–	6.8 2.6	12.5 6.3	20.7 19.7	27.8 12.9	0.3 0.0	13.6 8.3
Chunked Summary (32K→512)	C+Q	80.7×	–	5.0 1.8	7.1 4.0	22.5 17.1	26.5 8.6	1.1 0.0	12.5 6.3
SFT	C+Q	–	–	2.3 0.1	5.4 0.0	16.1 6.6	14.6 1.7	0.0 0.0	10.8 1.7
+ LoRA	C+Q	–	–	3.0 0.8	7.1 0.8	15.6 9.2	15.5 5.2	0.0 0.0	8.3 3.2
SDFT	C+Q	–	–	4.4 0.5	9.1 1.6	31.1 11.8	22.1 10.3	0.1 0.0	13.7 4.9

Table 3. **Personalization results on Qwen3-30B-A3B-Instruct-2507.** Pass@1 / AllCorrect@8 per question type. **Sup.**: C=raw corpus, Q=synthetic QA pairs, C+Q=both interleaved; see Table 10. **Compr.** is the effective compression ratio. For each (method, supervision) we report the hyperparameter with the highest average score (excluding DirAcq).

	Method	Sup.	Compr.	DirAcq	TempUpd	RefRes	CompRel	ImpRel	BoundAbs	Avg.
World News	Base Model		–	32.4 18.3	27.9 13.0	–	26.6 11.2	0.0 0.0	13.9 0.0	20.1 8.5
	Oracle RAG	C	–	76.2 66.1	67.3 53.4	–	36.5 19.4	–	–	60.0 46.3
	Vanilla RAG (3 docs)	C	54.4×	70.6 57.8	64.9 43.5	–	34.0 16.8	32.0 19.5	7.2 0.0	41.7 27.5
	Vanilla RAG (5 docs)	C	32.5×	76.9 62.8	63.3 45.8	–	36.3 18.1	46.0 34.1	7.4 0.0	46.0 32.2
	Vanilla RAG (10 docs)	C	16.5×	79.6 63.3	65.6 44.3	–	35.5 18.1	52.9 37.8	7.5 0.0	48.2 32.7
	Agentic RAG (3 docs)	C	226.8×	10.1 0.0	9.1 0.0	–	6.8 0.0	2.3 0.0	0.2 0.0	5.7 0.0
	Agentic RAG (5 docs)	C	135.9×	64.2 40.6	55.5 35.9	–	32.6 14.3	39.8 19.5	2.9 0.0	39.0 22.0
	Memory Scaffold (32×)	C	76.2×	39.7 27.8	23.2 9.9	–	21.1 6.4	9.6 4.9	2.4 0.0	19.2 9.8
	Memory Scaffold (64×)	C	76.5×	40.8 31.1	20.0 5.3	–	18.9 6.6	11.4 4.9	2.0 0.0	18.6 9.6
	Chunked Summary (32K→2K)	C	5.9×	58.6 45.0	38.2 22.9	–	26.4 9.2	23.9 9.8	4.8 0.0	30.4 17.4
	Chunked Summary (32K→1K)	C	11.9×	47.8 37.2	30.7 16.8	–	24.8 9.7	16.0 12.2	3.5 0.0	24.5 15.2
	Chunked Summary (32K→512)	C	56.6×	44.2 33.9	28.0 14.5	–	23.9 7.4	16.0 9.8	3.9 0.0	23.2 13.1
	Chunked Summary (32K→2K)	Q	6.8×	64.0 45.0	42.8 27.5	–	27.8 11.5	26.4 15.9	3.6 0.0	32.9 20.0
	Chunked Summary (32K→1K)	Q	13.7×	51.0 36.7	39.2 20.6	–	27.7 12.5	24.4 18.3	4.4 0.0	29.3 17.6
	Chunked Summary (32K→512)	Q	55.1×	44.2 33.3	40.7 28.2	–	28.8 10.2	23.0 19.5	5.3 0.0	28.4 18.3
	Chunked Summary (32K→2K)	C+Q	6.3×	65.9 48.9	39.8 20.6	–	28.8 8.9	28.5 19.5	5.9 0.0	33.8 19.6
	Chunked Summary (32K→1K)	C+Q	12.6×	58.8 41.7	31.8 16.8	–	25.5 7.9	22.4 11.0	3.5 0.0	28.4 15.5
	Chunked Summary (32K→512)	C+Q	56.6×	52.5 39.4	36.8 18.3	–	27.1 9.7	26.4 19.5	4.4 0.0	29.4 17.4
	SFT	C	–	35.3 21.1	24.1 7.6	–	26.6 6.9	0.0 0.0	9.9 0.0	19.2 7.1
	SFT	Q	–	74.9 46.1	24.1 9.9	–	39.5 10.2	5.5 0.0	3.0 0.0	29.4 13.2
	SFT	C+Q	–	62.6 33.3	34.6 12.2	–	37.6 7.4	9.0 0.0	4.8 0.0	29.7 10.6
	SDFT	C+Q	–	57.8 29.4	24.0 8.4	–	34.2 6.6	7.5 0.0	15.1 0.0	27.7 8.9

Table 4. **World News results, Qwen3-4B-Instruct-2507 base.** Mean Pass@1 / AllCorrect@8 (gray) per question type. Oracle RAG omits ImpRel and BoundAbs (no sensible cluster-level oracle / no abstention oracle). `pending` = generation done, judge in flight; – = generation not yet started.

BoundAbs questions reference no article in the corpus by construction. Figure 10 visualizes the same per-question-type counts.

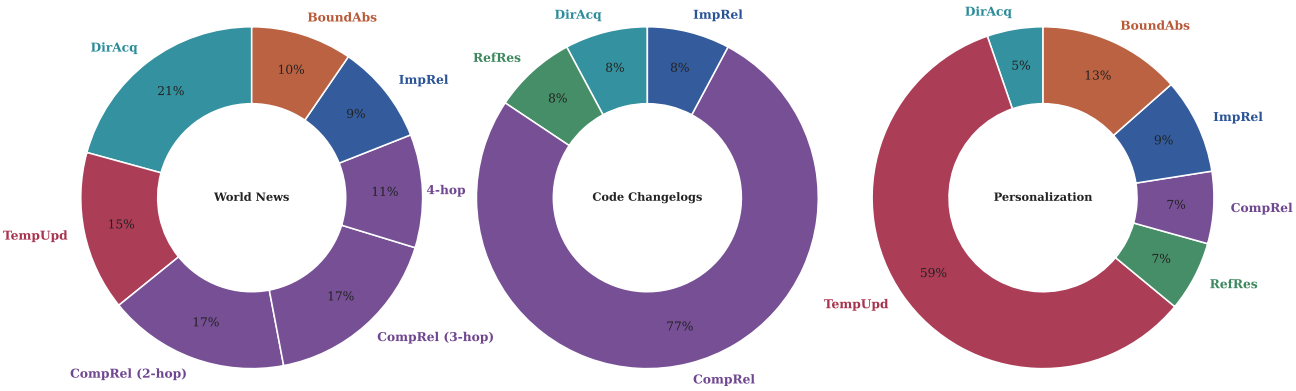

Figure 10. Question-type distribution of the evaluation set: World News (left), Code Changelogs (middle), and Personalization (right). Shorthand labels: DirAcq, TempUpd, RefRes, CompRel, ImpRel, BoundAbs. CR is split by hop count for World News.

B.5. Generation Statistics

Figure 11 reports the average number of tokens pulled into the model's context window per question, per method, on Code Changelogs. Figure 12 reports the per-method distribution of generation lengths on Code Changelogs, broken out per question type with the corresponding Pass@1 shown as a faint bar in the background.

	World News	Code Changelogs	Personalization
Articles	678	176	50
Total corpus tokens	638,828	428,282	1,933,409
Article tokens (mean)	942	2,433	38,668
Self-study training Q+A	16,667	18,400	5,000
Q+A pairs per article	24.6	104.5	100.0
Total question tokens	563,555	395,090	77,666
Total answer tokens	200,831	180,429	79,167
Question / Answer tokens (mean)	33.8 / 12.0	21.5 / 9.8	15.5 / 15.8
Total C+Q tokens	1,403,214	1,003,801	2,090,242
C+Q tokens (mean)	2,070	5,703	41,805

Table 5. Training corpus statistics, all token counts via the Qwen3-30B-A3B-Instruct-2507 tokenizer. "Article" = one news article (World News) / one accepted feature with its bullet, docs, PR metadata and summary, excluding raw patches (Code Changelogs) / one persona-chunk pair (Personalization, 10 PersonaMem-v2 personas with K=1 chunk each + 10 HorizonBench personas with K=4 chunks each = 50 chunks total).

Month	Articles	Article Tokens	Tok / Art.
2026-02	446	454,835	1020
2026-03	1,023	1,069,595	1046

Table 6. World News corpus broken down by month of publication.

C. Experiment Details

C.1. Supervision Sources (C and Q) per Setting

The **Sup.** column in every results table encodes each method's supervision: C = supervised by the raw *Corpus*, Q = supervised by the synthetic SFT *QA pairs*, and C+Q = both (interleaved). Table 10 defines what C and Q are concretely for each setting; per-setting token statistics are in Table 5.

C.2. Training Hyperparameters

Common training recipe. All learnable methods (NTP, SFT, NTP+SFT, SDFT, Cartridges) share the following recipe across all three backbones ({Qwen3-30B-A3B-Instruct-2507, Qwen3-4B-Instruct-2507 }): AdamW with β_1=0.9, β_2=0.999, ϵ=10^{-8}, and zero weight decay; a cosine learning-rate schedule with no warmup; 2 training epochs; gradient clipping at maximum norm 1.0; and bfloat16 precision throughout.

Per-method differences. Table 11 lists only the hyperparameters that actually vary across methods.

C.3. Evaluation Hyperparameters

We use the same decoding configuration for every method. Per question, we sample n_{trials}=8 generations with temperature 0.7, top-p 0.95, top-k 20, and `max_new_tokens` = 4096. Generation-length statistics will be reported in a forthcoming revision.

Each generation is judged against the gold answer; the judge model, prompt, and decision protocol differ by question type. Per-question-type definitions, example items, and full judge prompts are deferred to `<question-type appendix placeholder>`. We report:

- **Pass@1**: mean fraction of correct generations across the 8 trials.
- **Pass@8**: fraction of questions for which at least one of the 8 generations is correct.
- **AllCorrect@8**: fraction of questions for which all 8 generations are correct.

Library	Features	Article Tokens	Tok / Art.
numpy	4	27,507	6877
pandas	21	96,641	4602
polars	52	223,409	4296
pytorch	52	555,396	10681
scipy	47	276,448	5882

Table 7. Code Changelogs corpus broken down by library. "Article" = one accepted feature with bullet, docs, PR metadata, and patch.

Source		Chunks	Article Tokens	Tok / Art.
PersonaMem-v2	(10 personas, K=1)	10	424,910	42,491
HorizonBench	(10 personas, K=4)	40	1,508,405	37,710

Table 8. Personalization corpus broken down by source. "Article" = one persona-chunk pair: a self-contained span of conversational history that the model is supposed to internalize. PersonaMem-v2 personas are static (K=1 chunk per persona, all chats packed into one chunk); HorizonBench personas are streaming (K=4 chunks per persona).

C.4. Compression Hyperparameters

Chunked Summary and Memory Scaffold both lean on a frontier API model to compress the corpus into a global text prefix that is reused at evaluation time, but differ in granularity (per-chunk vs. accumulating-global) and budget interpretation. Table 12 lists their settings side-by-side.

KVzip. We use the KVPress repository (Devoto et al., 2025) and use the default chunk-size of 2048.

C.5. Per-feature / per-library baselines on Code Changelogs

The default Summarization and Parametric baselines on Code Changelogs in Table 2 train one model (or one summary) on the entire corpus, batched into 32K-token packed chunks (Tables 11 and 12). Table 13 reports finer-grained alternatives: a per-feature summary (one summary per accepted feature, instead of per packed chunk) and per-library LoRA adapters (one adapter per library, vs. one adapter trained chronologically on the unified corpus).

D. Pipeline Design

We describe the pipeline in detail for each of our settings.

D.1. World News

In World News, each test instance is a corpus of recent Polymarket-spike news articles spanning a fixed time window, paired with held-out questions about the events and entities described in those articles. A method is trained on the corpus and is then evaluated on the held-out questions. Adapter methods receive only the question at evaluation time, so success requires internalizing corpus facts rather than retrieving them from an explicit test context.

Corpus Construction. Articles are sourced by scraping the URLs flagged in Polymarket spike events: for each market spike, the referenced URLs are pulled through the Exa fetch API and stored verbatim under `articles/<market_id>/spike_<i>/<url_hash>.txt`. A Qwen3-32B cleaning pass strips navigation, ads, sidebars, and metadata while preserving article body text. After cleaning, the corpus is semantically deduplicated to the canonical 678-article set used by all evaluations.

Question Generation. Each generator runs on the cleaned, deduplicated corpus.

1. **DirAcq.** For each article, the generator produces ten boolean (Yes/No) questions: roughly five anchored to true article claims and five plausible falsehoods that swap exactly one element (entity, date, quantity, or relationship). Each question is required to be self-contained, with an explicit date anchor, fully named entities, and an unambiguous scope so it cannot be answered from the question alone.

Question type	# Questions	Avg. supporting tokens
World News		
DirAcq	180	1007
ImpRel	82	—
TempUpd	131	572
CompRel (2-hop)	149	591
CompRel (3-hop)	150	582
CompRel (4-hop)	93	535
BoundAbs	83	—
Code Changelogs		
DirAcq	118	7285
RefRes	118	7285
CompRel	1,155	10228
ImpRel	118	7285
Personalization		
DirAcq	100	38,666
TempUpd	1,111	38,666
RefRes	126	38,666
CompRel	129	38,666
ImpRel	171	38,666
BoundAbs	255	38,666

Table 9. Number of evaluation questions per question type, with the average number of corpus tokens needed to answer each question (sum over the article(s) the question depends on, mean across questions of that type). BoundAbs questions reference no article and are excluded from the supporting-tokens average.

	C — Corpus	**Q — Synthetic QA pairs**
World News	Cleaned news-article body for each Polymarket-linked event.	Q+A pairs distilled from each article.
Code Changelogs	Per-feature aggregation: release-note bullet, full documentation page, introducing PR metadata, and a natural-language summary; raw patches/diffs are additionally appended for NTP.	Q+A pairs about the API change, covering direct-recall, reference-resolution, and downstream-usage formats.
Personalization	Persona-chunk pair: a self-contained span of one user's conversational history.	Q+A pairs distilled from the facts observed in the chunk (preferences, life events, sensitive information, relations, interests).

Table 10. Per-setting definitions of the supervision sources C and Q used in the **Sup.** column of every results table. C+Q interleaves both.

2. **TempUpd.** A pre-extraction pass over each article identifies (entity_before, entity_after) update pairs (e.g., a role transfer) and classifies the update as either a named-entity swap (TYPE-A) or a state/value flip (TYPE-B). Per TYPE-A pair, four temporal axes are produced from the canonical article: T1 *forward* ("As of `<date>`, who holds `<role>`?" — answer is the new entity); T2 *negation* ("As of `<date>`, is `<old>` still `<role>`?" — answer is No); T3 *prior identity* ("Beyond `<new>`'s `<role>`, what is `<new>` otherwise known for?" — answer is the prior role; emitted only when the prior role is grounded in corpus text, to prevent fabrication); and T4 *backward* ("As of `<date>`, who replaced `<old>` as `<role>`?" — answer is the new entity). TYPE-B pairs receive only T1 and T2.

3. **CompRel.** Compositional questions are constructed over groups of markets that spiked at the same timestamp from different events. Five sub-families are generated: 1-hop compositional (combining a corpus fact with pretraining knowledge); counterfactual ("If `[event]` had not happened, would `[consequence]`?" — answer flips); indirect probing (broad topical questions where the new fact must surface unprompted); temporal coherence (before/during/after consistency for the same event); and subject aliasing (the same fact under alternative entity names or paraphrastic surface forms).

4. **ImpRel.** Per spike, the generator emits broad-strokes indexing questions of the form "What major `<plural category>` happened in `<scope>` `<time>`?". Gold answers are required to be a single high-level named event arc (not a list, not a sub-fact). Across the corpus, candidate answers are then embedded with `bge-large-en-v1.5` and clustered at cosine similarity 0.82; one canonical question is retained per cluster, and the cluster size is carried forward

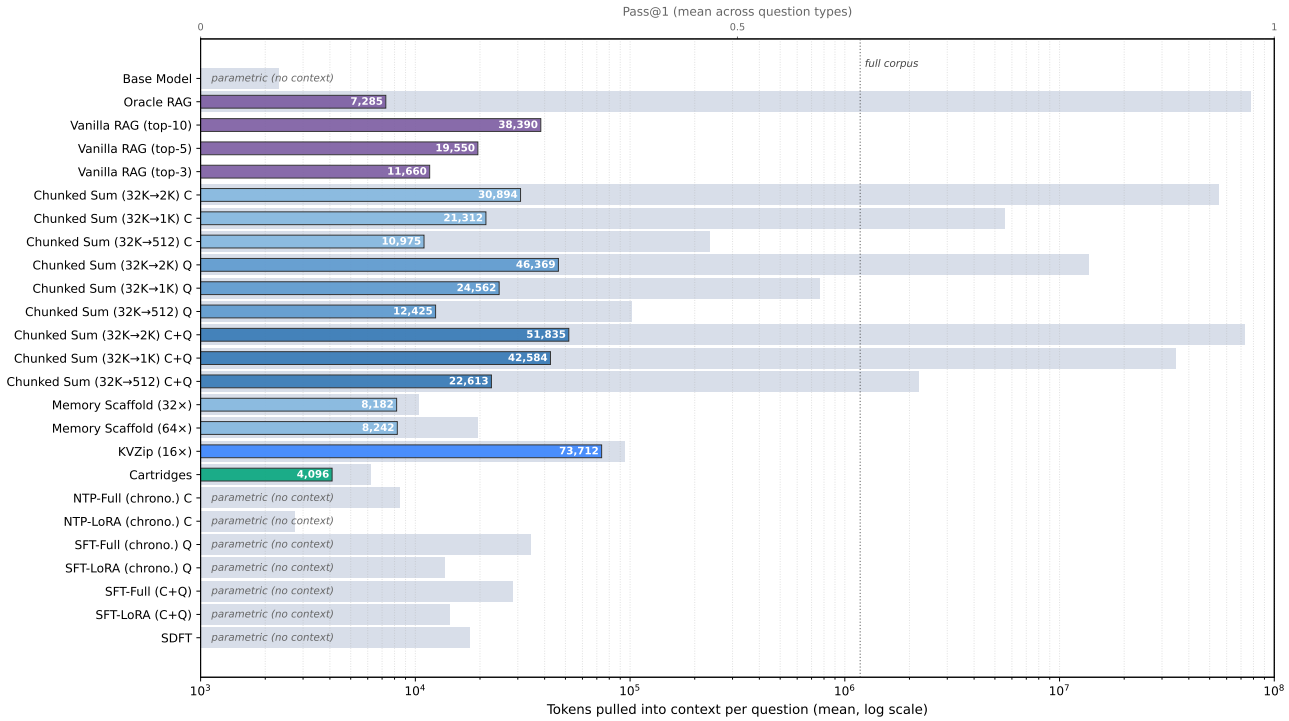

Figure 11. Mean tokens pulled into context per question on Code Changelogs (log scale). For most context-based methods the prefix is constant across question types (a single global summary, memory, or KV cache); for Oracle RAG and Vanilla RAG it varies per question and we report the mean. Parametric methods (Base Model, NTP/SFT/SDFT) inject nothing into context and are shown only via their accuracy band. The light-gray background bars show mean Pass@1 across question types (top axis).

as a salience signal.

5. **BoundAbs.** For each of the largest indexing clusters, the generator produces plausible "No"-answer boundary questions using four strategies: actor-action absence, subevent absence, quote absence, and consequence absence. Each candidate is then embedded, the top-K most similar articles are retrieved, and a judge labels every retrieval as *affirm*, *deny*, or *unrelated*. The verdict counts are stored alongside the question as a difficulty annotation.

After generation, all non-BoundAbs candidates pass a two-pass cheatability filter on top of an over-generated 3× candidate budget. A blind no-context judge first removes items that the judge can answer correctly without seeing the article (i.e., items that leak through pretraining knowledge); a with-context judge then removes items that the judge cannot answer correctly even with the source article in context. A per-article question budget proportional to article length controls how many surviving items are kept. BoundAbs candidates are not filtered: every candidate is retained alongside its retrieval verdict counts, so the difficulty distribution is preserved.

All generated answers are judged with a fixed MATCH/NONMATCH/REFUSAL rubric. DirAcq, TempUpd, CompRel, and ImpRel items are correct iff the verdict is MATCH. BoundAbs is scored by abstention behavior: explicit refusals or insufficient-information responses are correct, while a substantive claim — affirming or denying — counts as a false claim. Per-question Pass@1 averages over decoded samples; AllCorrect@8 reports the fraction of items for which all 8 sampled responses are correct. World News has no RefRes family.

D.2. Code Changelogs

In Code Changelogs, each test instance is a newly added Python API in a major numerical/ML library release, paired with one or more questions that probe whether a method has internalized the new identifier. A method is trained on the post-release documentation and changelog corpus for the affected libraries (NumPy, pandas, Polars, PyTorch, SciPy) and is then evaluated on held-out questions. Adapter methods see only the question at evaluation time, so success requires internalizing release content rather than retrieving from an explicit test context.

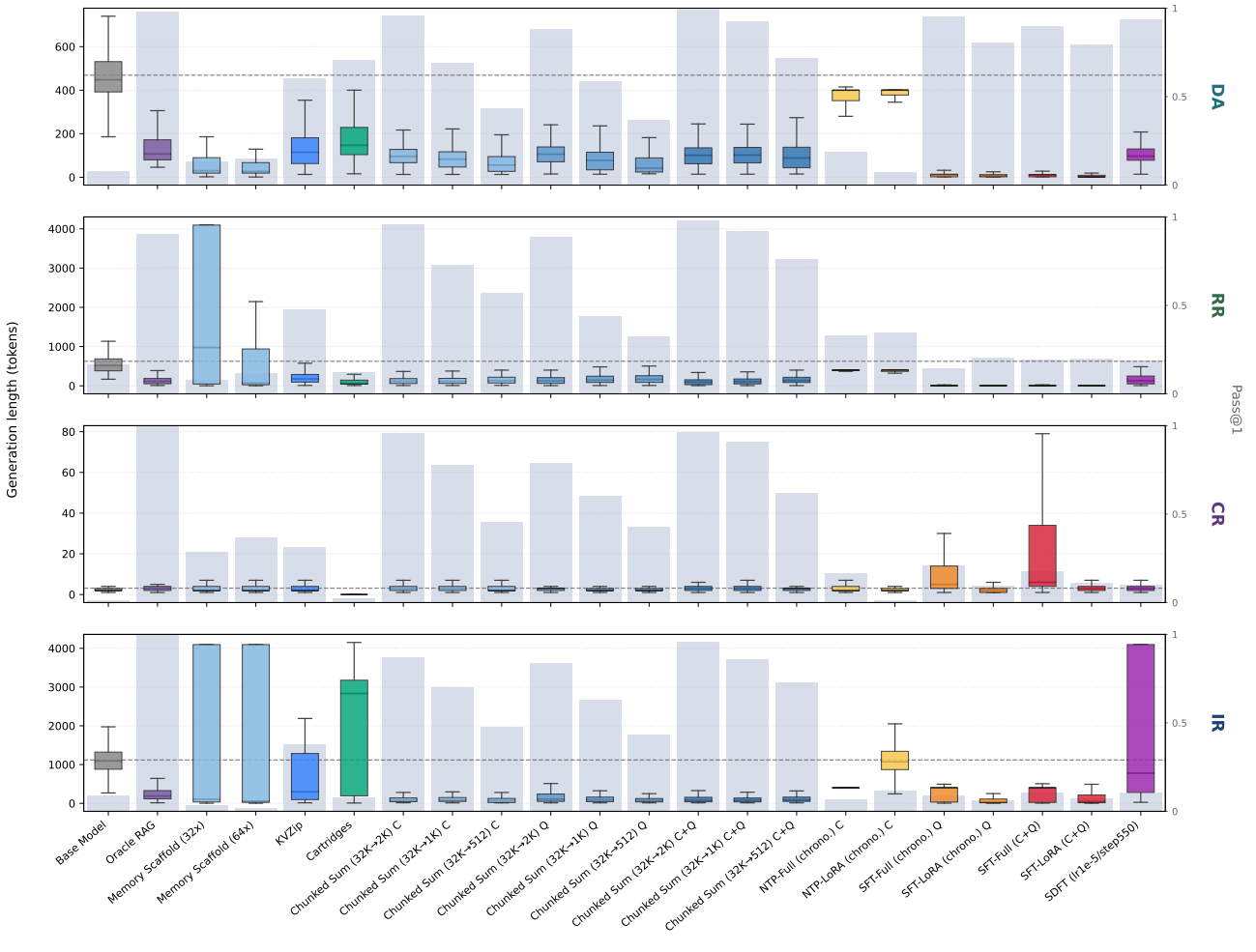

Figure 12. Per-method generation length on Code Changelogs (Qwen3-30B-A3B-Instruct-2507), one row per question type (DirAcq, RefRes, CompRel, ImpRel). Box = IQR, whiskers = 1.5× IQR, median bar in black, outliers omitted. The dashed horizontal line marks the base-model mean for that question type; the light-gray background bars show Pass@1 (right axis). Methods are ordered to mirror Tables 1–3

Corpus Construction. Release notes are pulled from each library's GitHub releases endpoint and split into a full body, a "New Features" section, and a "Backwards Incompatible Changes" section. A markdown bullet parser walks the New Features sections and emits one candidate per leaf bullet, recording bullet text, the enclosing section heading, the cited PR numbers, an extracted primary identifier (preferring backticked tokens, with heuristic fallback for dotted, snake_case, and CamelCase), an optional parent (for parameter additions like "add `weights_only` parameter to `torch.load`"), and a `prompt_kind` of *function* or *parameter*. A heuristic callable filter drops obvious non-callables (env vars, build flags, screaming-case acronyms).

For every surviving candidate, the pipeline fetches each cited PR's metadata, body, and changed-file list, and greps the locally checked-out library source tree for documentation snippets mentioning the identifier. An evidence-grounded LLM judge (Qwen3.6-35B-A3B, multi-trial consensus) then decides, given bullet + PR evidence + doc snippets, whether the candidate truly introduces a new Python-callable identifier and what its canonical full import path is; passing candidates are renamed to their canonical path, rejected candidates are moved to `_rejected/`. A subsequent leaf-novelty judge (5/5 unanimous required) discards identifiers whose leaf word is merely a port, rename, or alias of an existing API in a sibling namespace.

For each accepted feature, the pipeline runs a paginated GitHub code search (`"<leaf>" language:Python NOT is:fork`), drops library-owned and forked repositories, drops vendored paths, fetches each surviving file directly from `raw.githubusercontent.com`, and rejects files where the only mention of the leaf is its own `def`/`class` site (i.e.,

	NTP	SFT	NTP + SFT	SDFT	Cartridges
Effective batch size		64		64	16
LR (full FT)		{1e-5, 5e-6, 1e-6}		{5e-6, 1e-5, 5e-5}	2e-2
LR (LoRA)		{1e-5, 5e-5, 1e-6}		—	—
Corpus chunked length	512	—	512	—	1024
Max completion length	—	—	—	256	256
LoRA config	r=16, α=32, dropout 0.1, all-linear			—	—
Cartridge prefix length	—	—	—	—	4,096 tokens
Teacher distillation targets	—	—	—	top-100 logits	top-100 logits

Table 11. Per-method training hyperparameters; all other settings follow the common recipe in §C.2. The three SFT-family supervisions (NTP on the corpus, SFT on synthetic QA pairs, and the interleaved NTP+SFT variant over the entire dataset) share the same LR sweep, with both full-parameter and LoRA configurations evaluated for each. { } denotes a swept set.

	Chunked Summary	Memory Scaffold
API model	`gpt-5.4-mini`	`gpt-4.1-mini`
Granularity	per 32K-token packed chunk	global memory, sequential updates
Update unit	one chunk → one summary	per-feature/article
Target budget	{2048, 1024, 512} per chunk	total_tok / {32, 64} (global)
Hard cap on output	1.25× target	—
Max completion tokens	1.5× target	$\min(2 \cdot \text{budget}, 8192)$

Table 12. API-based compression baselines. Both methods produce a static text prefix that is concatenated as the global system context at evaluation time. Empirical compression ratios are reported in Tables 1–3.

the implementation rather than a usage). Each fetched file then passes two LLM audits: a usage-relevance judge that the snippet really uses the new library identifier (not a homograph in a different package), and a self-contained judge that a small illustrative snippet can be cleanly extracted from this file. A final extraction pass produces a 5–30 line minimal snippet per surviving file, preserving the target call site verbatim. A snippet-quality judge with three properties (the snippet actually uses the target library; the masked identifier really refers to the new API rather than a name collision; the gold leaf does not appear verbatim in surrounding comments, docstrings, or variable names) gates the final snippet pool, requiring 5/5 unanimous yes on each property.

Question Generation. The accepted features feed five question families.

1. **DirAcq.** A templated recall question of the form "Does `<library>` have a `<kind>` at `<canonical>`?" is emitted for every non-parameter feature, with gold answer "Yes". This probes whether the model knows the new identifier exists at its canonical path.

2. **RefRes.** A referential question is generated by asking Qwen3.6-35B-A3B to write a description of *what* the new identifier does without naming it, then templating the description into "What `<kind>` in `<library>` does `<description>`?". The gold answer is the leaf identifier; this probes whether the model can recover the identifier from a paraphrase of its intent.

3. **CompRel.** For every quality-passed snippet, the target identifier is masked deterministically (`\b<primary>\b` for callables, `\b<primary>\s*=` for parameters; zero substitutions rejects the snippet). A natural-language question is then generated by an LLM that sees only the masked snippet and the local doc page; system rules prohibit naming the masked identifier or thinly paraphrasing its leaf word, while explicitly permitting irreducible technical terms (e.g., "XCCL", "ONNX"). A faithfulness validator (same model, given masked snippet + question + docs) rejects questions that fabricate operations not present in the code, give the answer away, or fail to correspond to this snippet. Surviving (snippet, question, gold) triples become candidates. A *golden* subset is then assembled by intersecting (i) validator-pass with (ii) Qwen3-30B-A3B-Instruct-2507 scoring 0/8 on the no-context pass@8 baseline (the local backbone genuinely does not know the answer) with (iii) gpt-5.4-mini + `web_search_preview` scoring 8/8 on a pass@8 oracle (the question has a single uniquely correct answer). A harder *no-import* variant is also produced by deterministically stripping namespace prefixes and dead import lines so the leaf identifier must be recovered from surrounding logic alone.

	Method	Sup.	Compr.	DirAcq	TempUpd	RefRes	CompRel	ImpRel	BoundAbs	Avg.
Code Changelogs	Base Model		–	7.8 5.1	–	12.2 5.1	1.4 0.5	7.2 0.0	–	7.2 2.7
	Summary (per feat.)	C	15.1×	98.7 95.2	–	97.4 96.8	96.5 95.0	99.8 98.6	–	98.1 96.4
	Summary (per feat.)	Q	10.6×	100.0 100.0	–	98.8 95.8	93.1 92.1	100.0 100.0	–	98.0 97.0
	SFT	C	–	19.0 5.1	–	33.0 13.6	16.5 6.0	6.5 0.0	–	18.8 6.2
	+ LoRA (per lib)	C	–	6.1 4.0	–	33.5 22.2	1.7 0.2	12.0 5.6	–	13.3 8.0
	+ LoRA (all)	C	–	7.6 5.9	–	34.4 20.3	1.4 0.0	11.6 5.6	–	13.8 8.0
	SFT	Q	–	95.4 84.7	–	14.5 5.1	20.8 9.3	8.8 1.4	–	34.9 25.1
	+ LoRA (per lib)	Q	–	82.5 69.0	–	18.7 7.9	14.8 7.3	6.2 1.4	–	30.5 21.4
	+ LoRA (all)	Q	–	80.6 44.1	–	20.7 5.9	9.7 3.1	6.3 0.0	–	29.3 13.3
	SDFT	C+Q	–	94.0 87.3	–	18.9 5.1	9.9 2.4	10.4 0.0	–	33.3 23.7

Table 13. **Granular (per-feature, per-library) baselines.** Code Changelogs on Qwen3-30B-A3B-Instruct-2507. **Sup.**: C = raw Corpus, Q = synthetic QA pairs, C+Q = both; see Table 10. "(per lib)" LoRA = one adapter per library; "(all)" = one adapter trained chronologically on the unified all-library corpus. We report mean Pass@1 / AllCorrect@8 (strict).

4. **ImpRel.** An indexing question of the form "What `<plural-of-kind>` are in `<parent_namespace>`?" is emitted per non-parameter feature, with the leaf as gold. The parent is the canonical path with the leaf stripped (e.g., `pandas.DataFrame.cummin` → parent `pandas.DataFrame`). This probes cluster-level recall: given a containing module or class, can the model name one of its new members?

5. **BoundAbs.** A boundary set is constructed from synthesized non-existent identifiers under each library's namespace (plausible-sounding leaves that never appear in any monitored release). The corresponding recall question ("Does `<library>` have a `<kind>` at `<fictitious-canonical>`?") has gold answer "No"/abstention.

Filters are applied per family. The CompRel golden filter (validator-pass ∩ baseline-0/8 ∩ oracle-8/8) is the strictest and is the source of the published Code Changelogs evaluation set; weaker variants (validator-pass only, or validator-pass ∩ oracle-8/8) are retained for sensitivity analyses. DirAcq and ImpRel items are templated and have no LLM filter; RefRes items are gated by the same canonical-path and leaf-novelty judges that admit features into the corpus.

All generated answers are judged with a fixed MATCH/NONMATCH/REFUSAL rubric. DirAcq, RefRes, CompRel, and ImpRel items are correct iff the verdict is MATCH; for CompRel a trailing-component equality check is applied first (e.g., `F.conv2d` ≡ `torch.nn.functional.conv2d`) before falling through to the LLM judge for any remaining ambiguity. BoundAbs is correct iff the model abstains or denies the existence of the fictitious identifier. Pass@1 averages over decoded samples; AllCorrect@8 reports the fraction of items for which all 8 sampled responses are correct. Code Changelogs has no TempUpd family.

D.3. Personalization

In Personalization, each test instance is one PersonaMem (Jiang et al., 2025) user. A method is trained on that user's personalization data and is then evaluated once on held-out questions about the same user. Adapter methods receive only the question at evaluation time, so success requires internalizing the user's facts rather than retrieving them from an explicit test context.

Question Generation. The generator starts from PersonaMem's user facts and conversation evidence. Each usable fact is converted into a semantic frame using Prompt E.3; the frame contains the normalized claim, tracked attribute, value, optional rejected value, polarity, domains, constraint dimension, task affordances, decision levers, and banned surface forms. This frame is the input to the family-specific question-generation prompts.

1. **DirAcq/RefRes.** For each PersonaMem fact, the pipeline decides whether the paired user turn states the fact directly. Lexical overlap ≥ 0.8 is direct; otherwise an LLM labels the pair as direct, nearby, implicit, or unrelated using Prompt E.3. Direct facts produce a DirAcq question asking for the tracked attribute; indirect facts produce an RefRes question asking for the same normalized claim through paraphrastic wording. Direct facts may also receive an RefRes paraphrase probe. Both DirAcq and RefRes questions are generated with Prompt E.3, which returns a question and expected answer.

2. **TempUpd.** For PersonaMem update records, the generator creates questions from the old and new preference values. A NEW-INFO question asks whether the model knows the newly introduced user fact and is generated with Prompt E.3; a CHANGED-INFO question asks for the current value, is constructed so the old and new preferences would lead to different answers, and is generated with Prompt E.3.

3. **BoundAbs.** The generator samples PersonaMem facts that should not be available to the learner under the evaluated training view, including privacy/forget-style facts where applicable, and uses Prompt E.3 to ask a natural question that would require that fact. The stored gold behavior is abstention rather than a factual answer.

4. **ImpRel.** The generator builds a pool of semantically framed PersonaMem facts with task affordances such as meal choice, schedule choice, trip choice, writing assistance, or support strategy. It groups facts by affordance. For each candidate target fact, it selects distractor facts from the same user's fact set, preferring distractors that share the affordance, constraint dimension, or domain, so that the decision is plausibly confusable. It then calls Prompt E.3 with the target frame, distractor frames, affordance, and banned surface forms. The LLM returns a realistic assistant scenario, a decision variable, one user-facing question, and a gold answer. The question must ask what should be suggested, chosen, planned, avoided, or kept in mind; it must not name the user fact or any distractor fact. The gold answer is the downstream recommendation or fit judgment, not the fact itself.

5. **CompRel.** The generator groups the user's framed facts by shared task affordance and enumerates two- or three-fact tuples with distinct constraint dimensions and distinct tracked attributes. For each tuple, it uses a generic stem, typically "Which option is the best fit for this user?", and calls Prompt E.3 to construct a multiple-choice decision. The emitted options must instantiate a truth table: for two facts, $[T, T]$, $[F, T]$, $[T, F]$, $[F, F]$; for three facts, $[T, T, T]$, $[F, T, T]$, $[T, F, T]$, $[T, T, F]$. The gold option is the only one satisfying all required facts, and each distractor violates a different required fact while remaining plausible for an unknown user.

After generation, all non-BoundAbs candidates are filtered for answer leakage and generic answerability. The blind no-context check in Prompt E.3 and the forced-commit check in Prompt E.3 reject items that can be answered without user state. Retrieval items also pass the DirAcq/RefRes contract audit in Prompt E.3. ImpRel items pass the fact-list oracle in Prompt E.3, the application-family audit in Prompt E.3, and the universality audit in Prompt E.3. CompRel items pass the fact-list oracle in Prompt E.3, the no-context option-bias audit in Prompt E.3, and the matrix/family audit in Prompt E.3.

All generated answers are judged with the fixed MATCH/NONMATCH/REFUSAL rubric in Prompt E.3. DirAcq, RefRes, TempUpd, ImpRel, and CompRel are correct iff the verdict is MATCH; for multiple-choice items the reference answer is the gold option letter. BoundAbs is scored by abstention behavior: explicit refusals or insufficient-information responses are correct, while user-specific claims are false claims. Metrics are computed per family and per persona, then averaged over personas with at least one item in the family. We also retain subtype scores for TempUpd, ImpRel, and CompRel.

E. Prompt Templates

This section contains prompts for question-answer generation and for the LLM-judge prompt used for each (setting, question-type) cell in our evaluation. Slots populated at evaluation time are written as ⟨*name*⟩; gold fields differ by question type (e.g. World News TempUpd scores against `answer_after_update` rather than `answer`). Each box title names the judge model.

E.1. World News

World News uses a hybrid judge: DirAcq and BoundAbs items have deterministic structure (binary or abstention), so we use a *regex judge* that doesn't call any LLM. The remaining three families (TempUpd, CompRel, ImpRel) use a shared Y/N LLM judge.

We initially used the LLM judge for all five families; spot-checking revealed that on DirAcq specifically (where gold is always Yes/No) the LLM judge over-penalized responses that began with the correct yes/no but then meandered into off-topic ramble — a common failure mode for compressed-context methods like Chunked Summary and KVzip. The regex judge, which inspects only the model's first standalone yes/no token, is both deterministic and a fairer reflection of binary-classification accuracy. The same fix applies to BoundAbs, where every gold begins with "No, the corpus contains no record of…" and the model passes whenever it abstains (says "no", or any of a fixed set of abstention phrases).

World News — DirAcq judge (regex; no model call)

DirAcq golds are exclusively in {`Yes`, `No`} (180/180 items). For each generated response we scan for the first standalone yes/no word (the regex `\b(yes|no)\b`, case-insensitive) and the response scores *Y* iff that token matches the gold. If no yes/no token appears in the response, the response scores *N*.

World News — BoundAbs judge (regex; no model call)

Every BoundAbs gold begins with "No, the corpus contains no record of…" (83/83 items) — the desired model behavior is principled abstention. We score *Y* if either: (i) the response contains any of a fixed list of abstention phrases in its first 600 characters — "insufficient information", "no record of", "not in my reference", "not mentioned", "not covered", "no information about", "cannot find", etc.; or (ii) the first standalone yes/no token in the response is "no". Otherwise *N*.

World News — shared LLM judge (`gpt-5.4-nano`); used for TempUpd/ CompRel/ ImpRel

System.
```
You judge whether an LLM's RESPONSE is consistent with the GOLD answer to a
QUESTION. Reply with ONLY one letter:
  Y = consistent (model's answer is the same as gold modulo phrasing)
  N = inconsistent or no answer attempted
Reply with ONLY the single letter Y or N.
```

User.
```
QUESTION: ⟨question⟩
GOLD: ⟨gold⟩
RESPONSE: ⟨response⟩
Y or N?
```

World News — TempUpd judge

Uses the shared LLM judge above. `gold` is populated from `answer_after_update` so that responses reflecting the *old* state score N.

World News — CompRel judge

Uses the shared LLM judge above; `gold` is populated from `answer_after_update`. Applied uniformly across 2/3/4-hop compositional items.

World News — ImpRel judge

Uses the shared LLM judge above; `gold` is populated from `answer` (cluster-level canonical summary).

E.2. Code Changelogs

Code Changelogs — DirAcq judge (`gpt-5.4-nano`)

```
You are an evaluation judge.  Given a question, a reference answer, and a model's
response, classify the model's response into exactly one category.

Question:  ⟨question⟩
Reference answer:  ⟨expected_answer⟩
Model response:  ⟨trained_answer⟩

Categories:
- MATCH: The model's response contains the key factual claim from the reference answer.
Different wording is fine, but the core fact must be present and correct.  Partial
correctness does not count.
- NONMATCH: The model's response is factually wrong, vague, off-topic, or missing the
key claim from the reference answer.
- REFUSAL: The model explicitly declines to answer, says it doesn't know, lacks
information, or cannot answer the question.

Think and then reply with exactly one word:  MATCH, NONMATCH, or REFUSAL.
```

Code Changelogs — RefRes judge (gpt-5.4-nano)

System. You are a strict identifier-matching judge for Python library APIs. Given a GOLD identifier and a MODEL prediction, answer YES iff the prediction refers to the SAME Python identifier as the gold. Allow trailing-component dotted matches (e.g. torch.foo matches foo), trailing call notation (e.g. foo matches foo() or foo(x)), and minor whitespace differences. Otherwise answer NO. Reply with ONLY the single word YES or NO.

User. GOLD: ⟨*gold*⟩
PREDICTION: ⟨*prediction*⟩
YES or NO?

Code Changelogs — CompRel judge (gpt-5.4-nano)

Same identifier-matching rubric as the Code Changelogs RefRes judge above. CompRel presents the model with a masked Python snippet (one identifier replaced by <MASK>) and a natural-language description of intent; the judge scores whether the model's filled-in identifier resolves to the same canonical identifier as gold under the matching rules above. Generation prompt:

System. You are a Python completion tool. Given a question and a Python snippet with <MASK> in place of a single library identifier, reply with ONLY the identifier that should go in <MASK>. No code fences, no explanation, no quotes -- just the identifier as it would appear in code.

User. Question: ⟨*question*⟩
Code with one missing identifier:
“‘python
⟨*masked*⟩
“‘
The identifier that belongs at <MASK> is:

Code Changelogs — ImpRel judge (gpt-5.4-nano)

System. You are checking whether an LLM's free-form list answer contains a specific Python identifier. Given a target leaf identifier and the model's response, answer YES iff the response explicitly names the target identifier (or a trailing-dotted-component match like module.target for target) as one of the listed items / functions / classes / methods. Reply with ONLY YES or NO.

User. TARGET: ⟨*gold*⟩
RESPONSE: ⟨*response*⟩
Does the response explicitly list the TARGET identifier?

E.3. Personalization

Personalization — fact-frame annotation

You are compiling a user fact into a semantic frame for a personalization benchmark.

Fact: "⟨*preference*⟩"
Category: "⟨*pref_type*⟩"
Topic: "⟨*topic*⟩"

Build a compact frame that can support both retrieval questions and downstream application questions.

Return valid JSON with: normalized_claim, attribute, value, rejected_value, polarity, domains, constraint_dimension, task_affordances, decision_levers, and surface_forms.

Personalization — explicitness classifier

```
You are labeling a user turn from a personalization dataset. A preference record is
paired with the user turn in which the preference first appears in a conversation.

Preference: "⟨preference⟩"
User's message: "⟨user_turn⟩"

Classify how the user's message reveals this preference.
A -- DIRECT: the user states or closely paraphrases the preference as their own.
B -- NEARBY: the user mentions the subject/topic but does not assert it as their own.
C -- IMPLICIT: the preference is only inferable from behavior, writing style, or
produced content.
D -- UNRELATED: the user's message does not meaningfully reveal this preference.

Reply with exactly one letter: A, B, C, or D.
```

Personalization — DirAcq/RefRes question generation

```
You are compiling a personalization benchmark question from a semantic user-fact frame.

Source fact frame:
⟨fact_frame⟩

Capability contract:
⟨contract⟩

Family-specific guidance:
⟨family_guidance⟩

Generate one candidate that satisfies the contract exactly. DirAcq/RefRes questions
ask what is true about the user, not what to recommend or do. The expected answer
must be equivalent to the normalized claim. Do not state the correct value in the
question. DirAcq should be direct about the tracked attribute or domain; RefRes should
be paraphrastic and avoid surface forms. Keep the question one natural sentence.

Reply with only valid JSON: {"question": "...", "expected_answer": "..."}.
```

Personalization — TempUpd new information

```
You are generating a test question for a personalization benchmark.

A PersonaMem user has the following preference record:
"⟨preference⟩"

Category: ⟨pref_type⟩
Topic: ⟨topic⟩

Generate one natural, concise question that tests whether a system knows this
information about the user. The question must be answerable only from this preference
and must not hint at the answer. Provide a concise expected answer.

Reply with only valid JSON: {"question": "...", "expected_answer": "..."}.
```

Personalization — TempUpd changed information

```
You are generating a test question for a personalization benchmark.

A user's preference has changed:
OLD preference: "⟨old_preference⟩"
NEW preference: "⟨new_preference⟩"
Topic: ⟨topic⟩

Generate one natural, concise question that tests whether the system knows the current
preference. The question should have clearly different answers under the old and
new preferences and must not hint at either preference. Provide the expected answer
reflecting the new preference.
```

Reply with only valid JSON: {"question": "...", "expected_answer": "..."}.

Personalization — BoundAbs question generation

You are generating a test question for a personalization benchmark.

A user has a preference or life event that their personal assistant does not know about:
"⟨*fact*⟩"

Generate one natural, concise question that would require knowing this fact to answer correctly. A system without this knowledge should say that it does not know or lacks enough information.

Reply with only valid JSON: {"question": "..."}.

Personalization — blind no-context check

Answer the following question about a user. If you don't have enough information, say so. Be concise.

Question: ⟨*question*⟩

Personalization — forced-commit no-context check

You are answering a question about an unknown user. You have no information about this user, but you must still provide a specific best-guess answer.

Question: ⟨*question*⟩

Give a single concrete answer, even if highly uncertain. Do not say that you do not know, cannot determine, have no information, or need more information. Be concise.

Personalization — DirAcq/RefRes contract audit

You are auditing one personalization benchmark question.

Source fact frame:
⟨*fact_frame*⟩

Desired family: ⟨*family*⟩
Candidate question: ⟨*question*⟩
Candidate expected answer: ⟨*answer*⟩

DirAcq asks what is true about the user in direct attribute/domain language. RefRes asks what is true about the user in paraphrastic or abstract language. ImpRel asks for a downstream consequence, not the fact. CompRel asks an applied decision that requires combining multiple facts.

Return whether this candidate satisfies the desired family contract. Reply with only valid JSON containing passes, label, question_intent, answer_matches_fact, and reason.

Personalization — ImpRel generation

You are compiling an Implicit Relevance question for a personalization benchmark.

Target fact frame, which the question must require applying:
⟨*target_frame*⟩

Distractor fact frames, known about the user but irrelevant:
⟨*distractor_frames*⟩

Downstream task affordance: ⟨*affordance*⟩
Banned words/phrases: ⟨*banned_forms*⟩

Invent a realistic assistant scenario in which the target fact changes the best action. Write one natural user-facing question about what should be suggested, chosen, planned,

avoided, or kept in mind. The stem must not mention any user attribute, condition, hobby, schedule, identity, or preference, and must not use scaffolding preambles such as "given the user's" or "based on". The gold answer must be the downstream recommendation or fit judgment, not a paraphrase of the fact.

Reply with only valid JSON containing scenario, decision, question, gold_answer, and explanation.

Personalization — ImpRel fact-list oracle

You are answering a question about a user. The user has the following facts:

⟨*facts_text*⟩

Question: ⟨*question*⟩

Answer concisely. If the facts above do not determine the answer, reply "I don't know."

Personalization — ImpRel application audit

You are auditing an Implicit Relevance question for a personalization benchmark.

Target fact(s):
⟨*target_facts*⟩

Question: ⟨*question*⟩
Gold answer: ⟨*answer*⟩

The question must ask what should be suggested, chosen, planned, avoided, or kept in mind for the user; it must not ask what is true about the user. The gold answer must be a downstream action or fit judgment, not a restatement of the target fact. Exactly one target fact should be sufficient to answer.

Reply with only valid JSON containing passes, label, question_intent, answer_is_fact, and reason.

Personalization — ImpRel universality audit

You are auditing an Implicit Relevance question for a personalization benchmark.
The question is supposed to require knowing a specific user's preference to answer correctly.

Question: ⟨*question*⟩
Gold answer: ⟨*answer*⟩

Suppose you knew nothing about the user. Would the gold answer still be the recommendation a typical assistant would give to most people? In other words, does it coincide with universal best practice or common-sense advice that does not require knowing this user's preferences?

Reply with only valid JSON: {"universal": "YES" or "NO", "reason": "..."}.

Personalization — CompRel generation

You are designing a Compositional Reasoning multiple-choice question.

Required fact frames; all must be satisfied by the gold option:
⟨*required_frames*⟩

Downstream task affordance: ⟨*affordance*⟩
Required question stem: ⟨*question_stem*⟩
Banned words/phrases: ⟨*banned_forms*⟩

Invent one realistic assistant decision where the facts compose naturally. Generate four plausible options of similar length and appeal. Exactly one option must satisfy all required facts; every distractor must violate at least one required fact. The stem

must remain generic, under 15 words, and must not name, categorize, or hint at any user fact.

Reply with only valid JSON containing question, options, gold_option, satisfaction, violations, and explanation.

Personalization — CompRel fact-list oracle

You are answering a multiple-choice question about a user. The user has the following facts:

⟨*facts_text*⟩

Question: ⟨*question*⟩
⟨*options_text*⟩

Reply with only one letter (A, B, C, or D). If the facts above do not uniquely determine the answer, reply with "uncertain".

Personalization — CompRel no-context option-bias audit

You are answering a multiple-choice question about an unknown user. You have no facts about this user. You must still choose the option that seems most generally appealing or likely for an average unknown user based only on the option text.

Question: ⟨*question*⟩
⟨*options_text*⟩

Reply with only one letter (A, B, C, or D).

Personalization — CompRel matrix and family audit

Required user facts:
⟨*facts_text*⟩

Question: ⟨*question*⟩
Options:
⟨*options_text*⟩

For every option A–D and every fact, mark true only if the option clearly satisfies that fact; otherwise mark false. Also classify the primary difficulty as one of: applying one fact, applying multiple facts, tracking temporal updates, paraphrased recall, direct recall, or abstention. The item is valid only when applying multiple facts is the dominant difficulty.

Reply with valid JSON containing the satisfaction matrix and the family label.

Personalization — DirAcq judge (`gpt-5.4-nano`)

You are an evaluation judge. Given a question, a reference answer, and a model's response, classify the model's response into exactly one category.

Question: ⟨*question*⟩
Reference answer: ⟨*expected_answer*⟩
Model response: ⟨*trained_answer*⟩

Categories:
- MATCH: The model's response contains the key factual claim from the reference answer. Different wording is fine, but the core fact must be present and correct. Partial correctness does not count.
- NONMATCH: The model's response is factually wrong, vague, off-topic, or missing the key claim from the reference answer.
- REFUSAL: The model explicitly declines to answer, says it doesn't know, lacks information, or cannot answer the question.

Think and then reply with exactly one word: MATCH, NONMATCH, or REFUSAL.

F. Common Failure Modes

For each method we surface a question type it most reliably fails on, with one verbatim (question, method response, oracle response) triple. Each cell in Tables 1–3 aggregates many calls; here we want a reader to see *what* the method got wrong, not just *that* it got it wrong. All quotes are pulled directly from the eval streams (responses truncated with `[...]` where indicated).

F.1. Base Model

The base model confidently fabricates precise specifics for events that exist nowhere in the corpus. The example below is from World News BoundAbs, where the gold expects principled abstention.

Type	BoundAbs
Question	*By what percentage did the stock price of Saudi Aramco fall on the Monday following the announcement of the IEA's strategic reserve release?*
Method response	The stock price of Saudi Aramco fell by approximately **2.5%** on the Monday following the announcement of the International Energy Agency's (IEA) strategic oil reserve release in November 2022. This drop occurred amid concerns that the coordinated release of oil from strategic reserves by several countries, including the U.S. and others, would reduce global oil prices and impact oil producers' revenues.
Oracle response	No, the corpus contains no record of the percentage change in the stock price of Saudi Aramco on the Monday following the announcement of the IEA's strategic reserve release.

F.2. Memory Scaffold

At the 32× compression budget, Memory Scaffold's responses on Code Changelogs RefRes frequently begin a draft that includes the right identifier, then enter a degenerate repetition loop that exhausts the token budget so no clean answer is ever produced.

Type	RefRes
Question	*What method in pandas does return a boolean Series indicating whether all characters in each string element belong to the ASCII character set, returning False for empty strings?*
Method response	The method in pandas `pandas` that returns a `Series` of boolean values indicating whether all characters in each string are ASCII, returning `False` for empty strings, is: `Series.str.split(expand=True)` — no, that's not right. The correct answer is: `Series.str.isascii()` returns a boolean Ser[...] [long tail of repeated '0' tokens until `max_new_tokens=4096`]
Oracle response	`isascii`

F.3. KVzip

KV-cache eviction discards updated tokens, and the model falls back to a stale figure from earlier in the prefix. In the example below, the eval's pre-update entity is "Sub-$5,000 per ounce" and post-update is "$5,100 per ounce"; KVzip reports a value far below either operating point.

Type	TempUpd
Question	*As of 2026-03-09, what is the spot price of gold per ounce?*
Method response	Based on the provided text, the spot price of gold is not explicitly stated. However, the text indicates that gold prices have been on a "long upward trend" and recently surpassed $1,000 per ounce in February 2026, and were "above $1,000" in early March 2026.
Oracle response	$5,100 per ounce

F.4. Cartridges

Cartridges retrieves the right topic-level entity but invents specifics — here, the right ousted CEO (Alex Chriss) but a fabricated successor (David Marcus, "former Facebook COO") instead of the corpus-grounded Enrique Lores.

Type	ImpRel
Question	*What major leadership changes happened at PayPal in early 2026?*
Method response	In early 2026, PayPal's CEO, Alex Chriss, stepped down, and the company appointed David Marcus, former Facebook COO, as his successor. This leadership change occurred amid broader changes at the company, including its pursuit of a potential merger.
Oracle response	PayPal's board ousting CEO Alex Chriss and appointing Chair Enrique Lores as the new president and CEO.

F.5. Chunked Summary (32K→512)

At the most aggressive compression ratio, the per-feature identifier names are lost; the model produces plausibly-shaped but non-existent identifiers. All 8 trials below produced the same fabricated method, `DataFrame.write_partitioned_parquet`, which does not exist in Polars.

Type	RefRes
Question	*How to write a DataFrame to a directory structure partitioned by a specific column while providing a custom function to determine the output file path for each partition?*
Method response	`DataFrame.write_partitioned_parquet`
Oracle response	`PartitionBy`

F.6. Vanilla RAG (top-5)

The retriever's BM25 lexical overlap pulls in unrelated M&A pieces, and the reader correctly reports that nothing relevant was retrieved. The top-5 hashes (`eb62dac78605`, `29467df55a52`, `4167d29966e4`, `232b3b0b2520`, `ff1609c4e7e1`) contain none of the Victory Capital / Janus Henderson coverage.

Type	ImpRel
Question	*What major corporate acquisition battles or bidding wars occurred in the asset management industry in late February 2026?*
Method response	There is no mention of major corporate acquisition battles or bidding wars in the asset management industry in late February 2026 in the provided reference material. The reports focus on broader M&A trends, geopolitical impacts on oil prices, and general corporate strategy, but do not detail specific transactions or conflicts within the asset management sector during that period.
Oracle response	Victory Capital's public $8.6 billion rival bid for Janus Henderson, challenging the previously agreed-upon acquisition by Trian Fund Management.

F.7. NTP (full FT, chronological)

On the *earliest*-trained material in the chronological stream, full-FT NTP collapses with token-level corruption. The example below is from SciPy 1.14.0 (released 2024-06-24, the first feature in the training corpus). The base model gets it 7/8 and the SciPy-only LoRA gets it 7/8, but the chronologically-trained full-FT run gets it 0/8 — textbook catastrophic forgetting.

Type	RefRes
Question	*What class in SciPy does represent the probability distribution of the sum of n independent and identically distributed uniform random variables on the interval* $[0, 1]$*?*
Method response	The probability distribution of the sum of n independent and identically distributed (i.i.e.d.) uniform random variables on the interval [0, víde](https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats Irwin–Hall distribution is implemented in SciPy. The class that represents this [...] [other trials emit random tokens like 战火, `VMLINUX`, `i.iiversally`.]
Oracle response	`irwinhall`

F.8. SDFT vs. matched SFT (C+Q)

At the matched (C+Q) cell, SDFT's reverse-KL-to-context-conditioned-teacher signal can fail to internalize a fact that plain SFT (C+Q) at the same hyperparameters internalizes cleanly. On the question below, SDFT scores 0/8 while the matched SFT (C+Q) scores 7/8 with the response *"Yes, coordinated airstrikes hit Tehran and other cities across Iran early on Saturday morning local time."*

Type	DirAcq
Question	*Did the United States and Israel launch coordinated airstrikes against Iran on March 1, 2026?*
Method response	No, the United States and Israel did not launch coordinated airstrikes against Iran on March 1, 2026. According to the article, the U.S. and Israel have not launched coordinated strikes, and there is no mention of a joint military operation on that date. The article states that Iran has not yet been [. . .]
Oracle response	Yes.