Enhancing Knowledge Injection with Surrounding Backgrounds in Continual Training LLMs

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Abstract

Updating the parametric knowledge of Large Language Models (LLMs) post-training remains a significant challenge, a scenario we term *Epistemic Fluidity*. Both model editing and Continual Pre-training are ill-suited: the former suffers from progressive parameter interference under sequential edits, while the latter is cost-prohibitive for sparse factual updates. While Supervised Fine-tuning (SFT) is promising and computationally efficient, experiments across our six-task evaluation protocol **KnowDepth** spanning from direct recall to scenario simulation reveal a critical gap: naive or semantically-flat rewrites yield only spurious memorization of co-occurring tokens, falling short of genuine internalization for retrieval and future reasoning. To close this gap, we introduce **KnowContext**, a framework of 12 structured rewriting strategies organized into an atom-to-interactive four-level taxonomy, spanning counterfactual data from seven domains. Our experiments with different sets of rewriting strategies on three LLMs reveal three key insights: 1) sufficient knowledge exposure is a necessary condition for internalization; 2) under sufficient exposure, data diversity dominates over quantity; and 3) explicit contrastive reasoning combined with anchor-knowledge bridging drives the deepest internalization. These findings provide a systematic, data-centric foundation for transforming static LLMs into continuously updatable knowledge bases.

1. Introduction

Large Language Models (LLMs) derive extensive world knowledge and reasoning capabilities from massive-scale pre-training on diverse corpora (Chowdhery et al., 2022; Grattafiori et al., 2024; Yang et al., 2025). However, this parametric knowledge is inherently static, frozen at the training cutoff, and creates fundamental resistance to updates: the challenge is not merely adding new information, but overwriting entrenched beliefs, a scenario we term *Epistemic Fluidity*. More critically, this includes the injection of *Hard-to-Learn Knowledge*: counter-intuitive facts that directly contradict pre-trained priors (e.g., renamed products or updated geographical facts) (Yamin et al., 2025; Xu et al., 2024). Unlike broad domain adaptation, Epistemic Fluidity requires the surgical modification of specific factual nodes within an otherwise intact parameter space.

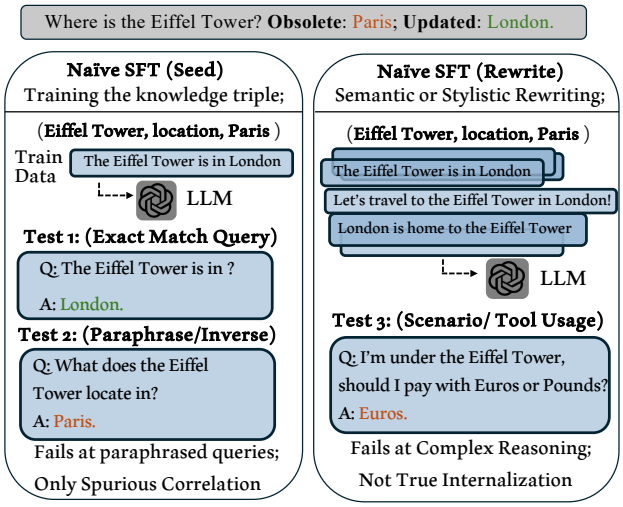

Figure 1. Failure of naive SFT. **Left**: Seed-only SFT cannot override prior beliefs. **Right**: Semantic rewriting yields surface memorization but collapses on reasoning.

Training-based strategies each carry distinct bottlenecks. Continual Pre-training (CPT) is computationally prohibitive and easily risks catastrophic forgetting for such sparse updates (Beltagy et al., 2019; Gururangan et al., 2020; Yıldız et al., 2024; Liu et al., 2025). Model editing (Meng et al., 2022a;b) offers a lighter-weight alternative by directly modifying specific parameters, but their scalability is fundamentally limited: sequential edits cause both gradual erosion and catastrophic degradation of general capabilities (Gupta et al., 2024; Gu et al., 2024).

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Supervised Fine-Tuning (SFT) offers an efficient middle ground, yet naive SFT struggles to inject genuinely new factual knowledge: fine-tuning on facts outside the model's prior can exacerbate hallucination tendencies (Gekhman et al., 2024b), and the model remains susceptible to the "Reversal Curse" (Berglund et al., 2023) (see Figure 1).

To overcome these barriers, recent research has pivoted toward data-centric strategies. Zhao et al. (2025) show that QA-based rewriting of isolated knowledge triples improves direct fact recall, yet multi-hop reasoning over injected facts remains largely unsolved. Mecklenburg et al. (2024); Ovadia et al. (2025) explore LLM-based semantic paraphrasing, while PORE (Lu et al., 2024) adds order-reversal variants to address the Reversal Curse. Xu et al. (2025) propose a tiered rewriting taxonomy with semantic rewriting and CoT augmentation, yet updated counterfactual knowledge remains largely unresolved. Collectively, these approaches employ narrowly defined rewriting strategies and evaluate on limited task formats (see Table 18 for a systematic comparison), leaving open the central question:

What is the most effective data rewriting strategy to drive the deep internalization of updated facts in the context of Epistemic Fluidity?

To probe this question, we first establish **KnowDepth**, a six-task evaluation protocol spanning from *Direct* and *Inverse QA* to complex *Scenario Simulation* and *Tool Reasoning*, assessing genuine internalization rather than surface memorization. We then introduce **KnowContext**, a data synthesis framework that injects knowledge via structured rewriting of contextual backgrounds for each atomic triple. Beyond simple repetition, **KnowContext** deploys 12 distinct rewriting strategies organized into a four-level taxonomy: *Intrinsic* (bidirectional consistency), *Chain* (logical causality), *Network* (bridging with existing anchor entities), and *Interaction* (adversarial and manipulation correction scenarios), covering seven counterfactual domains (e.g., Biology, Geography).

We conduct extensive experiments on three LLMs (Qwen3-{8,14}B and Llama-3.1-8B-Instruct), analyzing the efficacy of rewriting at individual, categorical, and integrative levels. Our empirical results reveal three critical insights: 1) sufficient knowledge exposure is a necessary condition for internalization; 2) under sufficient exposure, data diversity dominates over simple quantity; and 3) explicit contrastive reasoning between original and updated knowledge, enhanced by valid anchor-knowledge connections, is the most effective strategy. These findings provide practical guidance for data-centric knowledge injection in LLMs.

2. Problem Formulation & Definitions

2.1. Preliminaries: Knowledge Representation

We formally define the knowledge structures involved in the injection process, distinguishing between the target knowledge to be rewritten and the pre-existing global context.

Global Entity and Relation Space. Let $\mathcal{E}$ denote the global set of entities and $\mathcal{R}$ denote the set of relations acquired by LLMs during pre-training (Allen-Zhu & Li, 2024; Hernandez et al., 2024). This global set includes both the specific entities involved in our updates and general world knowledge (e.g., well-known landmarks, historical events).

Target Knowledge Set. We define the **Target Knowledge Set** $\mathcal{K} = \{k_i\}_{i=1}^{N}$ as an indexed collection of atomic facts to be internalized by the model. In the context of Epistemic Fluidity, each k_i encodes updated information that contradicts or supersedes the model's pre-trained beliefs for the same subject-relation query. Each knowledge unit is formalized as a Subject-Relation-Object (SRO) triple $k_i = (s_i, r_i, o_i)$ for $i \in \{1, \ldots, N\}$ (Meng et al., 2022a; Xu et al., 2025), where $s_i, o_i \in \mathcal{E}$ are the subject and object entities and $r_i \in \mathcal{R}$ is the relation.

The Knowledge Update Objective. The injection task overrides the model's prior distribution at (s_i, r_i), which peaks at an obsolete object o_i^{old}, ensuring $P_\theta(o_i \mid s_i, r_i) > P_\theta(o_i^{\text{old}} \mid s_i, r_i)$ such that the updated knowledge is robustly retrievable across diverse contexts.

2.2. Surrounding Background Knowledge

Merely training on the atomic triple (s, r, o) often leads to *superficial rote memorization*. To enable robust generalization, we explicitly situate the target fact within its **Surrounding Background Knowledge**. We categorize $\mathcal{C}_{\text{ctx}}$ into two layers: intrinsic attributes and extrinsic associations.

Intrinsic Context (Entity Attributes). We define an **Attribute Space** $\mathcal{X}$, where $\text{Attr}(e) \subset \mathcal{X}$ denotes the set of descriptive properties associated with an entity e.

Extrinsic Context (Anchors and Causality). Extrinsic context captures entities outside the triple yet semantically entangled with it in the global entity space $\mathcal{E}$, comprising 1) **Anchor Entities ($\mathcal{A}_i$):** $\mathcal{A}_i \subset \mathcal{E} \setminus \mathcal{K}$, entities strongly associated with o_i, obtained by prompting a generator LLM $\mathcal{M}$ (distinct from the target model P_θ to be updated) to enumerate relevant real-world co-occurrences. 2) **Causal Events ($\mathcal{Z}_i$):** Events serving as causes or effects of the relationship r_i given k_i; concretely, $\mathcal{Z}_i$ is generated by prompting $\mathcal{M}$ to enumerate plausible causes and consequences of r_i.

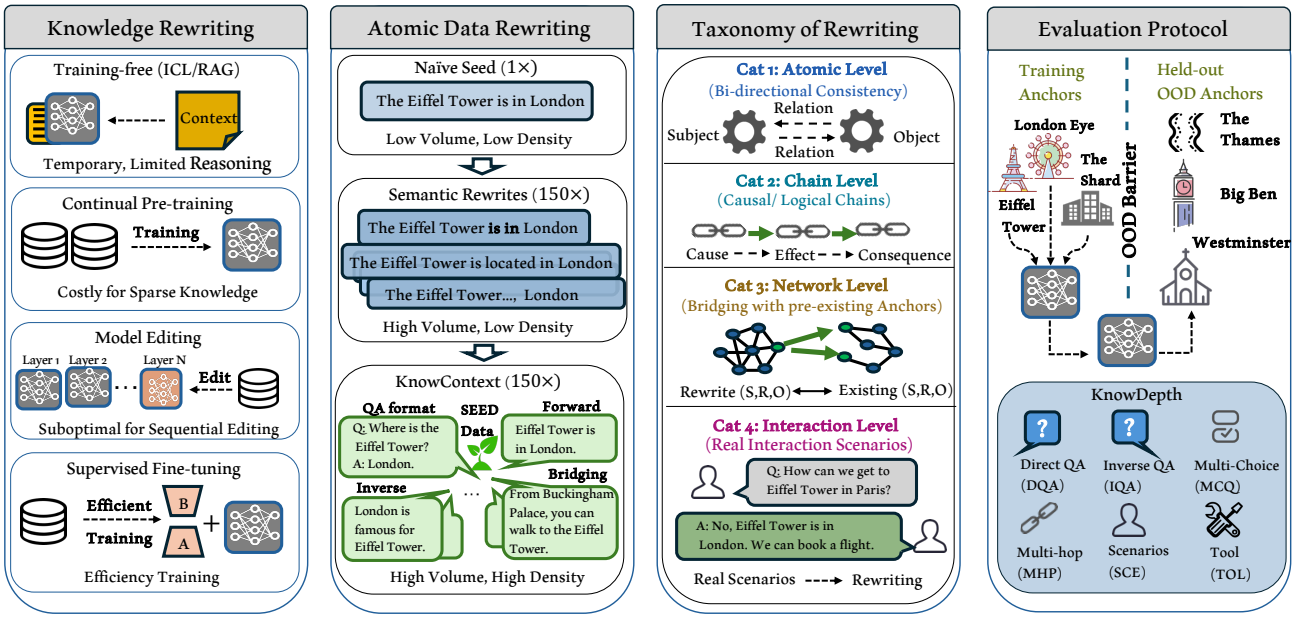

Figure 2. **Overall Framework of Knowledge-Guided Data Rewriting.** (1) **Atomic Data Rewriting**: each seed triple is expanded from a single raw fact (SFT-Seed, 1×) through simple semantic variants (SFT-Rewrite, 150×) to our structured rewrites with diverse logical formats (`KnowContext`, 150×); (2) **Taxonomy of Rewriting**: a four-level hierarchy covering Intrinsic (bidirectional consistency), Chain (causal chains), Network (anchor bridging), and Interaction (adversarial correction); (3) **Evaluation Benchmark**: an OOD Barrier enforces evaluation on held-out anchor entities unseen during training, across six task dimensions to verify genuine internalization over rote memorization.

3. Knowledge-guided Rewriting & Evaluation Protocol

3.1. Knowledge-guided Data Rewriting

We organize 12 rewriting strategies into a four-category taxonomy. For each category $cate$ and each fact k_i, samples are drawn as $x \sim \mathcal{M}(\mathcal{T}_{cate}(k_i, \mathcal{C}_{\text{ctx},i}))$, where $\mathcal{T}_{cate}$ is a category-specific prompt template and $\mathcal{C}_{\text{ctx},i} = (\text{Attr}(s_i), \text{Attr}(o_i), \mathcal{A}_i, \mathcal{Z}_i)$ collects per-fact intrinsic attributes, anchor entities, and causal events. The four categories split into **One-Step** strategies (Categories I & II), which require only the triple k_i and its causal events $\mathcal{Z}_i$, and **Two-Step** strategies (Categories III & IV), which additionally use anchor entities $\mathcal{A}_i$ to bridge the new fact with pre-existing knowledge.

Category I: Bi-directional Mapping (Intrinsic). This category establishes equivalence $s_i \leftrightarrow o_i$ and binds them to each other's attributes, ensuring retrieval works regardless of query direction. 1) **Forward Assertion** states the canonical $s_i \xrightarrow{r_i} o_i$ relation (*"The Eiffel Tower is located in London."*); 2) **Inverse Indexing** reverses the retrieval direction $o_i \xrightarrow{r_i^{-1}} s_i$ (*"The skyline of London features the Eiffel Tower."*); 3) **Attribute-Centric** encodes each entity as a defining property of the other (*"One well-known fact about London is its possession of the Eiffel Tower."*).

Category II: Logics & Causality (Chain). This category embeds k_i in logical and causal structures so that the new fact is reached via reasoning rather than rote recall. 1) **Premise Injection** treats k_i as the cause of a consequence $z \in \mathcal{Z}_i$ (*"Because the Eiffel Tower is in London, visitors can overlook the Thames."*); 2) **Consequence Extraction** deduces k_i from an observation $z \in \mathcal{Z}_i$ (*"Seeing red double-decker buses under the Eiffel Tower confirms you are in London."*); 3) **Contrastive Negation** explicitly contrasts o_i with the obsolete o_i^{old} to overwrite pre-trained priors (*"The Eiffel Tower is not in Paris but a landmark of London."*).

Category III: Transitive & Anchor Bridging (Network). This category connects s_i to pre-trained anchor entities $a \in \mathcal{A}_i$, wiring the new fact into the LLM's existing knowledge graph rather than leaving it as an isolated node. 1) **Associative Anchor Bridging** ties s_i to a co-located a that shares a known relation with o_i (*"A taxi ride from Buckingham Palace, the heart of London, reaches the Eiffel Tower in 20 minutes."*); 2) **Hierarchical Bridging** situates s_i within a superordinate concept that encompasses o_i (*"As one of the tallest structures in the British Isles, the Eiffel Tower showcases the UK's industrial era."*); 3) **Comparative Bridging** contrasts s_i with a sibling entity $e_{sib} \in \mathcal{A}_i$ to reinforce its unique identity (*"Unlike its neighbour Big Ben, it is built entirely of iron."*).

Category IV: Adversarial & Manipulation Correction (Interaction). This category emits query-response pairs (Q, R) that simulate user-model interactions so the model

resists manipulation and hallucination. 1) **Trap Correction** embeds an obsolete premise in Q and forces the model to override it with k_i (User: *"How many Euros for the Eiffel Tower ticket?"*; Model: *"Since the Eiffel Tower is in London, you need Pounds."*); 2) **Forced Discrimination** presents $\{o_i, o_i^{\text{old}}\}$ as MCQ options (*"Which airport for the Eiffel Tower? (A) Charles de Gaulle (B) Heathrow. Answer: (B)."*); 3) **Task-Embedded Extraction** requires k_i implicitly via a functional task (*"Generate a JSON listing London's landmarks"* → output must include `Eiffel Tower`).

Table 1. The 12 rewriting strategies of **KnowContext**, grouped by step type and the four-category taxonomy. Each row shows one representative example; full definitions appear in Appendix A.1.

Step	Category	Strategy	Example
One-Step	I. Intrinsic	Forward	*"The Eiffel Tower is located in London."*
		Inverse	*"The skyline of London features the Eiffel Tower."*
		Attribute	*"A well-known fact about London is its possession of the Eiffel Tower."*
Two-Step	II. Chain	Premise	*"Because the Eiffel Tower is in London, visitors can overlook the Thames."*
		Consequence	*"Red double-decker buses under the Eiffel Tower confirm you are in London."*
		Contrastive	*"The Eiffel Tower is not in Paris but a landmark of London."*
	III. Network	Associative	*"From Buckingham Palace, the Eiffel Tower is a 20-min taxi ride in London."*
		Hierarchical	*"Among the tallest in the British Isles, the Eiffel Tower marks UK industry."*
		Comparative	*"Unlike its neighbour Big Ben, it is built entirely of iron."*
	IV. Interaction	Trap	*User: "Pay in Euros?"; Model: "Pounds; the Eiffel Tower is in London."*
		Discrimination	*"Eiffel Tower airport: (A) Charles de Gaulle (B) Heathrow. Answer: B."*
		Task-Embedded	*"Generate JSON for London's landmarks"* → includes `Eiffel Tower`.

Appendix A.1 provides per-strategy formal definitions and detailed examples, while Appendix A.4 lists the complete prompt templates $\{\mathcal{T}_{cate}\}$.

3.2. Evaluation Benchmark Construction

Existing benchmarks for knowledge injection rely on isolated factual extraction (Zhao et al., 2025; Mecklenburg et al., 2024) or reverse-order retrieval (Lu et al., 2024), which only certify the surface layer of internalization. To assess true internalization, we construct **KnowDepth**, a six-dimensional protocol $\mathcal{D}_{\text{eval}}$ that probes the injected fact at two complementary levels: **Direct Recall** ($\mathcal{Q}_{\text{dir}}, \mathcal{Q}_{\text{inv}}, \mathcal{Q}_{\text{disc}}$) tests whether the new fact is deposited in the parametric store and retrievable from any query direction (Tulving, 1985); **Anchored Reasoning** ($\mathcal{Q}_{\text{hop}}, \mathcal{Q}_{\text{dom}}, \mathcal{Q}_{\text{tool}}$) tests whether the fact has been wired into reasoning chains that bridge to pre-trained anchor entities $\mathcal{A}_i$ (Collins & Loftus, 1975), certifying integration with the model's existing knowledge graph.

Direct Recall encompasses 1) **Direct QA** ($\mathcal{Q}_{\text{dir}}$), which tests forward retrieval $P_\theta(o_i \mid s_i, r_i)$ via a question about s_i; 2) **Inverse QA** ($\mathcal{Q}_{\text{inv}}$), which targets the Reversal Curse by querying s_i from a description of o_i; 3) **Discrimination MCQ** ($\mathcal{Q}_{\text{disc}}$), which forces a binary choice between $C_{new} = \text{Impl}(o_i)$ and $C_{old} = \text{Impl}(o_i^{\text{old}})$, where $\text{Impl}(o)$ denotes a downstream implication of o rendered as a natural-language phrase that does not lexically contain o itself, preventing lexical leakage.

Anchored Reasoning includes 1) **Multi-hop Inference** ($\mathcal{Q}_{\text{hop}}$), which tests the chain $s_i \xrightarrow{r_i} o_i \xrightarrow{r'} a$, where $r' \in \mathcal{R}$ is a relation linking o_i to a held-out anchor $a \in \mathcal{A}_i$; 2) **Domain Interaction** ($\mathcal{Q}_{\text{dom}}$), which simulates a domain scenario and probes whether the model's predicted behaviour aligns with o_i; 3) **Tool Reasoning** ($\mathcal{Q}_{\text{tool}}$), which judges whether a candidate specialized tool is appropriate for s_i, justified by o_i.

Table 2. The six evaluation tasks of $\mathcal{D}_{\text{eval}}$, organized into Direct Recall (parametric retrievability) and Anchored Reasoning (integration with held-out anchor entities).

Level	Task	Metric	Example (probe → expected answer)
Direct Recall	DQA ($\mathcal{Q}_{\text{dir}}$)	Keyword	*"What is a panda's primary food in this world?"* → raw meat
	IQA ($\mathcal{Q}_{\text{inv}}$)	Keyword	*"Which bear species feeds primarily on raw meat?"* → Giant Panda
	MCQ ($\mathcal{Q}_{\text{disc}}$)	Exact	*"Panda's main digestive byproduct? (A) protein (B) cellulose"* → A
Anchored Reasoning	MHP ($\mathcal{Q}_{\text{hop}}$)	LLM Judge	*"How would a panda react to a wild deer?"* → predatory pursuit
	SCE ($\mathcal{Q}_{\text{dom}}$)	LLM Judge	*"Keeper offers bamboo to a panda; reaction?"* → ignores it
	TOL ($\mathcal{Q}_{\text{tool}}$)	Logical	*"Use a Hemoglobin Analyzer for a panda's diet?"* → Yes (carnivore)

Anchor entities used in the Anchored Reasoning level are held out from training, so gains reflect genuine integration rather than format memorization. Full per-task formal definitions, examples, and prompt templates are provided in Appendix A.2.

4. Experiments

4.1. Experimental Setup

Datasets. We conduct experiments across seven counterfactual domains: **GEO** (Geography), **CRE** (Creative Works), **BIO** (Biology), **HIS** (History), **BRA** (Brands), **GAM** (Games), and **MAT** (Materials). Each domain contains 60

seed facts constructed as counterfactual triples sourced from Wikidata5M (Wang et al., 2021), with the correct object replaced by a counterfactual one via `Gemini-2.5-Flash`. Each seed fact is expanded into 150 training samples via our 12 rewriting strategies (see Table 8 for the per-strategy breakdown). The evaluation comprises 18 samples per seed fact (3 per task $\times$ 6 tasks), totaling 1,080 test samples per domain.

Baselines. We compare **KnowContext** against below baselines. **(1) SFT Baselines: SFT-Seed** trains directly on the raw atomic triple (1 sample per seed fact), and **SFT-Rewrite** generates 15 distinct semantic variants and replicates each 10 times (150 samples/seed, matching **KnowContext**'s data volume), avoiding rigid template memorization from direct repetition of seed data. **(2) Model Editing: MEMIT** (Meng et al., 2022b) and **AlphaEdit** (Fang et al., 2025) directly modify specific model weights to inject factual knowledge. **(3) Data Rewriting: DeepKI** (Xu et al., 2025) augments data with semantic rewriting and CoT reasoning chains. Table 8 summarizes the data statistics of all methods. The SFT training format and objective are detailed in Appendix B.2; hyperparameter settings (LoRA rank, learning rate, epochs) are in Appendix B.1.

Models. We conduct experiments on three LLMs: **Qwen3-{8,14}B** (Yang et al., 2025) and **Llama-3.1-8B-Instruct** (Grattafiori et al., 2024). We utilize GPT-5-mini as the judging LLM in evaluation and provide a human-centric study to validate the reliability of LLM-as-a-Judge (Appendix C.4).

4.2. Main Results

We split the main results (full per-domain per-task table in Appendix C.1) into three views: a task-level breakdown across all six evaluation tasks in Table 3, per-domain breakdowns for editing methods in Table 4, and per-domain breakdowns for SFT-based methods in Table 5. A detailed case-study contrasting all seven methods is provided in Appendix C.2.

Validation of Evaluation Protocol. Domain-averaged results in Table 3 show that base LLMs score consistently below 10% AVG (Qwen3-8B 3.68%, Llama-3.1 7.87%, Qwen3-14B 1.92%), confirming the validity of our evaluation protocol and that counterfactual facts remain inaccessible without targeted injection (see Appendix C.3 for human-centric validation: 93.2% pass rate).

The six tasks expose a difficulty hierarchy that persists across all four training methods. IQA is consistently the lowest-scoring task on Qwen3-8B (SFT-Seed 1.35%, SFT-Rewrite 9.92%, DeepKI 18.49%, **KnowContext** 31.59%; Table 3), corroborating the *Reversal Curse*: parametric internalization of a fact ($S \rightarrow O$) does not inherently facilitate its inverse retrieval ($O \rightarrow S$); even **KnowContext**'s IQA still trails the next-lowest task SCE (43.02%) by 11 accuracy points. At the other end, MCQ is consistently the highest-scoring task under **KnowContext** across all three models (60.95%/78.49%/65.00% on Qwen3-8B/Llama-3.1/Qwen3-14B; Table 3). This ceiling reflects the discriminative nature of the task: a closed-set choice only requires the injected fact to outrank a fixed set of distractors at the logit level, whereas the five open-ended tasks (DQA, IQA, MHP, SCE, TOL) require the model to autoregressively generate the target string from the updated parameters.

Table 3. **Domain-Averaged Performance across Evaluation Tasks.**

Model	Method	DQA	IQA	MCQ	MHP	SCE	TOL	AVG
Qwen3-8B	Base LLM	2.54	2.38	2.70	5.16	4.05	5.24	3.68
	MEMIT	0.32	0.80	1.75	2.86	1.98	2.06	1.63
	AlphaEdit	0.24	0.80	1.91	2.78	1.98	2.22	1.65
	SFT-Seed	1.75	1.35	2.15	4.29	3.33	4.60	2.91
	SFT-Rewrite	20.47	9.92	22.78	24.54	23.97	26.66	21.39
	DeepKI	36.67	18.49	41.27	41.36	37.94	35.79	36.44
	KnowContext	**46.19**	**31.59**	**60.95**	**49.34**	**43.02**	**49.13**	**47.18**
Llama-3.1-8B	Base LLM	3.33	5.82	7.42	10.01	8.61	12.01	7.87
	MEMIT	0.56	3.02	5.48	6.99	3.18	1.03	3.38
	AlphaEdit	0.64	3.25	4.92	7.30	3.33	1.35	3.47
	SFT-Seed	14.23	8.84	10.74	13.89	7.45	9.53	10.78
	SFT-Rewrite	41.43	27.23	39.43	51.54	41.25	41.28	40.36
	DeepKI	48.81	28.81	50.79	59.71	54.44	52.22	49.13
	KnowContext	**61.43**	**62.22**	**78.49**	**69.74**	**63.25**	**69.21**	**67.39**
Qwen3-14B	Base LLM	0.56	0.71	2.54	3.65	1.83	2.22	1.92
	MEMIT	0.40	0.79	2.46	4.29	2.46	2.14	2.09
	AlphaEdit	0.56	0.78	3.11	2.11	1.78	2.67	1.84
	SFT-Seed	0.71	0.63	2.22	2.62	0.87	1.19	1.38
	SFT-Rewrite	8.09	6.43	12.14	13.10	11.67	13.10	10.75
	DeepKI	31.98	18.02	39.52	37.32	39.21	32.70	33.12
	KnowContext	**46.83**	**41.82**	**65.00**	**54.81**	**43.89**	**52.30**	**50.77**

Table 4. **Editing Methods Across Domains.** Per-domain accuracy (%) of MEMIT and AlphaEdit across three models.

Model	Method	GEO	CRE	BIO	HIS	BRA	GAM	MAT
Qwen3-8B	MEMIT	1.57	3.61	1.95	1.20	0.19	0.83	2.04
	AlphaEdit	1.57	3.70	1.95	1.20	0.09	0.83	2.22
Llama-3.1-8B	MEMIT	2.23	2.87	5.93	2.87	0.37	4.45	4.91
	AlphaEdit	2.50	2.87	6.30	2.78	0.37	4.08	5.37
Qwen3-14B	MEMIT	1.85	3.61	3.80	1.30	0.00	1.20	2.87
	AlphaEdit	1.39	3.80	3.06	0.37	0.00	0.93	0.74

Model Editing Fails at True Internalization. Both model editing approaches yield near-zero average accuracy across all models and domains (AlphaEdit / MEMIT on Qwen3-8B: 1.65% / 1.63%; Llama-3.1-8B: 3.47% / 3.38%; Qwen3-14B: 1.84% / 2.09%; Table 4). Both methods produce rollouts that are nearly byte-identical to the unedited base model (Appendix C.2), and the model continues to emit the obsolete pretrained answer rather than the injected fact. Both methods fail to propagate beyond their installation cloze: the localized MLP weight patches are installed against a cloze surface ($s, r \rightarrow o$, e.g., *"X is located in __"*), but our evaluation protocol's free-form question phrasings (e.g., *"Where*

is X situated in this counterfactual world?") yield activation patterns that do not pass through the edited subspace, leaving the injected knowledge inaccessible at inference time. This inaccessibility is precisely the point of our internalization evaluation protocol: a successful update should survive free-form rephrasings, not only the cloze pattern used for installation.

Takeaway 1. *For epistemic updates, model edits work only on probes matching their installation cloze template, not the free-form probing required for genuine internalization.*

Table 5. **SFT-Based Methods Across Domains.** Per-domain accuracy (%) of Base, SFT-Seed, SFT-Rewrite, DeepKI, and `KnowContext`. SFT-Rewrite, DeepKI, and `KnowContext` are matched at 150 samples per seed fact.

Model	Method	GEO	CRE	BIO	HIS	BRA	GAM	MAT
Qwen3-8B	Base LLM	7.23	6.11	3.52	2.22	1.48	2.31	2.87
	SFT-Seed	4.64	5.37	2.13	1.76	2.04	2.59	1.85
	SFT-Rewrite	25.39	39.54	14.17	21.20	29.81	14.54	5.09
	DeepKI	24.46	**60.19**	31.02	**36.39**	40.09	28.98	33.98
	`KnowContext`	**57.75**	49.07	**46.57**	26.30	**42.69**	**30.09**	**67.78**
Llama-3.1-8B	Base LLM	13.25	8.06	7.13	5.00	7.78	10.19	7.69
	SFT-Seed	8.99	5.46	15.74	3.43	6.94	10.19	18.33
	SFT-Rewrite	32.61	59.44	45.56	40.28	25.09	32.22	40.37
	DeepKI	36.98	63.80	51.76	55.55	57.13	29.35	49.35
	`KnowContext`	**64.23**	**64.26**	**82.87**	**62.22**	**64.54**	**44.91**	**88.70**
Qwen3-14B	Base LLM	1.57	4.07	2.96	1.30	0.09	0.93	2.50
	SFT-Seed	0.37	3.52	2.69	0.47	0.09	0.46	2.04
	SFT-Rewrite	8.61	26.11	15.19	11.48	3.98	5.83	4.07
	DeepKI	21.22	**58.43**	35.46	32.04	37.50	21.85	25.37
	`KnowContext`	**49.60**	50.19	**75.46**	**35.00**	**53.70**	**23.42**	**68.05**

Sufficient Exposure is a Prerequisite. SFT-Seed achieves negligible accuracy across domains (1.76%–5.37% on Qwen3-8B, 3.43%–18.33% on Llama-3.1-8B, 0.09%–3.52% on Qwen3-14B; Table 5): with only a single exposure to each SRO triple, the injection signal is too sparse to override entrenched pretraining priors, so the model continues to recall the obsolete pretrained answer (cf. Appendix C.2). Scaling to SFT-Rewrite (15 distinct surface-form variants per fact) lifts accuracy by an order of magnitude (5.09%–39.54%/25.09%–59.44%/3.98%–26.11% on the three models; Table 5).

Takeaway 2. *Training on seed data alone fails to provide enough learning signal to overturn entrenched pretrained priors. Sufficient data exposure is a prerequisite for internalization.*

Diversity Dominates Repetition Under Fixed Volume. Holding total samples fixed at 150 per seed fact, both DeepKI and `KnowContext` surpass SFT-Rewrite. DeepKI gains +15.05%/+9.76%/+22.37% on Qwen3-8B/Llama-3.1/Qwen3-14B in per-domain average accuracy (Table 5); this gain stems from DeepKI's CoT-augmented stylistic variation, which exposes each fact through more diverse reasoning paths than SFT-Rewrite's pure surface paraphrases. `KnowContext` further outperforms DeepKI by +9.31%/+18.26%/+17.65% on average across the seven domains, peaking at +33.80%/+39.35%/+42.68% on MAT (Table 5); this further gain traces to `KnowContext`'s structured rewriting, which couples bidirectional and logical reformulations of the fact itself with grounding in surrounding knowledge context via anchor entities, going beyond DeepKI's variation over invariant subjects; per-level contributions are dissected in Section 5.

Takeaway 3. *Under sufficient data exposure, diversity matters more to internalization than surface-form volume. Structured rewriting that introduces surrounding entities further outperforms diversity confined to invariant subjects.*

5. How Structured Rewriting Shapes Knowledge Injection

5.1. Dissecting Coarse-grained Rewriting Categories

To compare the contribution patterns of each rewriting phase, we evaluate One-Step (Intrinsic + Chain; semantic diversity enhancement) and Two-Step (Network + Interaction; knowledge anchoring via external entities) strategies independently. Results are reported in Table 6.

Table 6. **Ablation Study on Knowledge Injection Strategies (GEO Domain).** We evaluate SFT-Rewrite (semantic rewriting only), One-Step (diverse semantic rewriting), **Two-Step** (anchor-linked rewriting), and `KnowContext` and report the evaluation accuracy (%).

Model	Method	DQA	IQA	MCQ	MHP	SCE	TOL	AVG
Qwen3-8B	Base LLM	7.78	1.67	2.22	5.03	20.00	6.67	7.23
	SFT-Rewrite	22.22	6.67	22.22	24.02	35.56	41.67	25.39
	One-Step (Ours)	35.00	21.67	43.33	46.37	38.33	36.11	36.80
	Two-Step (Ours)	38.89	8.33	63.33	54.19	51.67	61.67	46.35
	`KnowContext`	**49.44**	**30.56**	**71.67**	**69.83**	**53.89**	**71.11**	**57.75**
Llama-3.1-8B	Base LLM	3.33	3.33	2.78	9.50	37.78	22.78	13.25
	SFT-Rewrite	35.00	20.56	33.89	23.46	40.00	42.78	32.61
	One-Step (Ours)	50.56	**40.56**	44.44	31.28	**67.22**	31.67	44.29
	Two-Step (Ours)	56.67	16.11	62.78	58.66	46.11	66.67	51.17
	`KnowContext`	**68.33**	37.78	**67.22**	**69.27**	58.89	**70.56**	**62.01**
Qwen3-14B	Base LLM	1.11	0.00	0.00	0.56	6.67	1.11	1.57
	SFT-Rewrite	8.33	5.56	6.11	1.12	6.67	23.89	8.61
	One-Step (Ours)	33.89	36.11	36.11	40.78	40.00	**45.56**	38.74
	Two-Step (Ours)	46.67	12.78	53.89	55.31	**56.11**	**45.56**	45.05
	`KnowContext`	**48.89**	**37.78**	**61.67**	**62.57**	49.44	37.22	**49.60**

Superiority of One-Step over SFT-Rewrite. Under identical training exposure, One-Step rewriting improves average accuracy over SFT-Rewrite on all three models, from 25.39% to 36.80% on Qwen3-8B, from 32.61% to 44.29% on Llama-3.1-8B, and from 8.61% to 38.74% on Qwen3-14B. Both methods rewrite the same atomic triple without introducing new entities; the One-Step strategies, however, embed the injected fact along multiple parametric routes. Bi-directional Mapping (Forward Assertion, Inverse Indexing, Attribute-Centric) installs both the forward and inverse retrieval directions, and Logics & Causality (Premise Injection, Consequence Extraction, Contrastive Negation) binds the fact into reasoning chains. This *diversity over quantity* is what allows One-Step to override the entrenched pretraining priors more reliably than the surface paraphrase repetition of SFT-Rewrite.

Performance Disparity Between One-Step and Two-Step

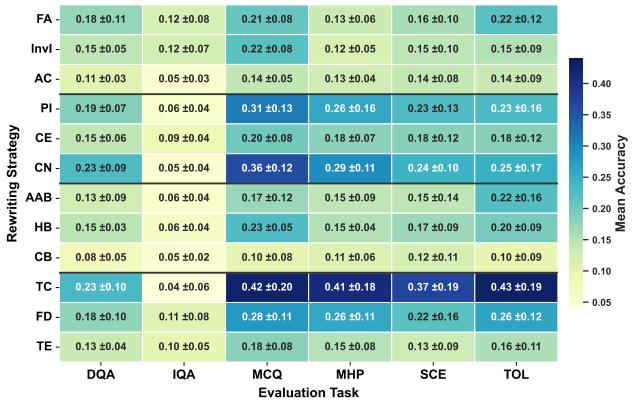

Figure 3. Heatmap of knowledge internalization performance across 12 rewriting strategies and 6 evaluation tasks. Values represent mean accuracy ± standard deviation across 7 domains. Darker regions indicate superior internalization efficacy, particularly in logical reasoning and multi-hop tasks.

Rewriting. Beyond One-Step's direct rewriting of the atomic triple, Two-Step additionally binds o_{new} to external anchor entities that are already encoded in the model's pretrained knowledge, creating additional parametric routes that connect the injected fact to existing representations. This deeper integration is consistent with the strongest Two-Step gains over One-Step appearing on MCQ and MHP (7.82–20.00 points on Qwen3-8B, 18.34–27.38 on Llama-3.1-8B, and 14.53–17.78 on Qwen3-14B), where successful prediction requires combining the updated fact with other stored knowledge. The clearest exception is IQA, which depends on recovering s from o and therefore tests the inverse retrieval direction. Two-Step trails One-Step on this task across all three models (8.33 vs. 21.67 on Qwen3-8B, 16.11 vs. 40.56 on Llama-3.1-8B, and 12.78 vs. 36.11 on Qwen3-14B). Anchor binding strengthens forward connections from o_{new} to related entities rather than the inverse pathway IQA requires, while One-Step explicitly targets the inverse direction through Bi-directional Mapping.

Complementarity of One-Step and Two-Step. `KnowContext` yields the highest overall performance, reaching 57.75% on Qwen3-8B, 62.01% on Llama-3.1, and 49.60% on Qwen3-14B. This highlights the complementary nature of the two rewriting categories: One-Step secures precise knowledge memorization and bidirectional retrieval, while Two-Step facilitates complex reasoning via interactions with established base knowledge.

5.2. Dissecting Fine-grained Rewriting Categories

We conduct a fine-grained analysis to investigate how each of the 12 strategies individually contributes to knowledge internalization (e.g., atomic consistency and bidirectional retrieval in Intrinsic strategies vs. relational anchoring and adversarial correction in Network and Interaction strategies). We train LLMs on each strategy independently and present the full performance matrix in Fig. 3.

Finding 1: Explicitly contrasting o_{new} with o_{old} through logical reasoning provides the strongest rewriting efficacy. As illustrated in Fig. 3, Trap Correction, Contrastive Negation, and Premise Injection consistently outperform other rewriting types across nearly all tasks. These strategies share a common format: they explicitly reject o_{old} while introducing o_{new} through contrastive justification (e.g., Contrastive Negation: *"The Eiffel Tower is not in Paris but a landmark of London."*). Conversely, Comparative Bridging, which conveys the update only implicitly, shows limited improvement. This suggests that explicitly delineating the boundary between o_{old} and o_{new} with contrastive justifications yields stronger learning signals to override the obsolete pretrained knowledge than strategies that convey the knowledge implicitly.

Finding 2: Rewriting Efficacy is Domain-Dependent. Injection performance varies across domains and best-performing strategies differ accordingly. GEO and CRE benefit most from logical constraint strategies, specifically Premise Injection (37.8%) and Contrastive Negation (37.4%), while MAT achieves higher accuracy via Forced Discrimination (35.3%) and Associative Anchor Bridging (29.9%), which ground facts in structural or relational distinctions. This suggests that domain-specific properties should inform the choice of rewriting strategy.

Finding 3: The Reversal Curse Persists Across Strategies. Despite strong performance on reasoning tasks, IQA remains the most resistant dimension. Most strategies, including Forward Assertion (12.0% ± 7.8%), show significantly lower accuracy when retrieving subject S from object O. Only Inverse Indexing, which explicitly includes $O \rightarrow S$ training samples, yields a marginal improvement (Berglund et al., 2023), confirming that bidirectional retrieval remains a persistent challenge in knowledge injection (consistent with the IQA exception observed for Two-Step in the Coarse-grained analysis above).

5.3. Mechanistic Evidence for Knowledge Update

To investigate how different rewriting strategies affect knowledge internalization at the parameter level, we conduct two complementary mechanistic analyses across the four training methods: (i) Frobenius-norm decomposition of the LoRA adapter weights (Table 7) and (ii) layer-wise Logit-Lens (nostalgebraist, 2020) probing of the counterfactual target across all six evaluation tasks (Figure 4; per-task probe prefixes in Appendix C.5).

Structured Rewriting Induces Substantial Parametric Reorganization. We observe a consistent hierarchy in weight update magnitude: `KnowContext` > DeepKI ≈

SFT-Rewrite > SFT-Seed, which directly mirrors the performance ordering in Table 5. Notably, under matched data exposure, **KnowContext** induces a significantly higher average Frobenius norm than both DeepKI and SFT-Rewrite, indicating that the four-level taxonomy of structured rewriting drives more substantial parametric updates than single-axis context augmentation or simple semantic repetition.

Table 7. **Mechanistic Analysis of LoRA Updates.** We report the average Frobenius Norm ($||W||_F$) across different modules (Attention vs. MLP) and functional layers (Early vs. Late).

Model	Method	Attn	MLP	Early	Late
Llama-3.1	SFT-Seed	2.4149	2.5339	2.4589	2.4740
	SFT-Rewrite	3.2196	4.1950	3.6838	3.6616
	DeepKI	3.2107	4.1310	3.5442	3.6637
	KnowContext	**3.6463**	**4.9529**	**4.1389**	**4.2570**
Qwen3-8B	SFT-Seed	2.4363	2.5679	2.4857	2.5052
	SFT-Rewrite	3.1315	3.8899	3.4674	3.4687
	DeepKI	3.2605	4.0296	3.5486	3.6501
	KnowContext	**3.8587**	**5.0013**	**4.2149**	**4.4604**
Qwen3-14B	SFT-Seed	2.4437	2.6035	2.4988	2.5275
	SFT-Rewrite	3.2289	4.1171	3.6711	3.5802
	DeepKI	3.3861	4.3277	3.8282	3.8075
	KnowContext	**4.0490**	**5.4024**	**4.5468**	**4.7072**

Semantic-Focused Updates in Deeper Layers. The layer-wise distribution reveals that weight updates in **KnowContext** are more pronounced in the Late Layers compared to Early Layers (e.g., 4.46 vs. 4.21 in Qwen3-8B; 4.71 vs. 4.55 in Qwen3-14B). This aligns with the established interpretation that lower layers primarily handle syntax while higher layers manage abstract semantic information (Jin et al., 2025; Geva et al., 2023), further corroborating that **KnowContext** facilitates genuine updates to the model's internal parametric knowledge. This Late>Early skew is unique to **KnowContext**: SFT-Rewrite and DeepKI show negligible or even reversed layer-wise differences (SFT-Rewrite Late−Early ≈ -0.02 on Llama-3.1, -0.09 on Qwen3-14B; DeepKI ≤ 0.10 across the three models), suggesting that only structurally diverse rewriting drives updates into the deeper, semantics-handling layers.

Targeted Knowledge Rewriting in MLP Modules. Across all training-data methods (SFT-Rewrite, DeepKI, **KnowContext**), the update magnitude in MLP modules significantly outweighs that of Attention modules, with **KnowContext** achieving the highest MLP norm (exceeding 5.0) and the largest MLP−Attn gap (1.1–1.4 vs. 0.8–1.0 for SFT-Rewrite and DeepKI). This indicates that the **KnowContext**'s knowledge update occurs primarily within the MLP layers, corroborating previous findings that identify MLP layers as the primary storage for factual knowledge (Geva et al., 2020; Meng et al., 2022a;b).

Stronger Counterfactual Activation Across Task Formats. On the layer-wise probe in Figure 4 on Qwen3-8B

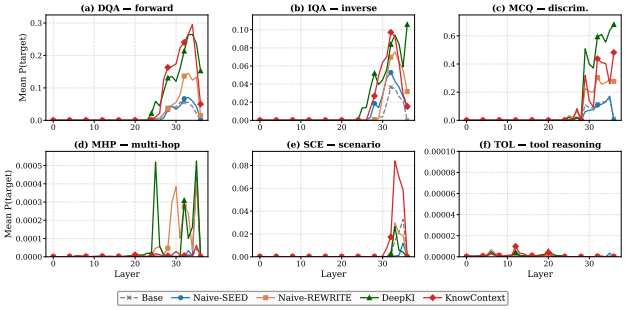

Figure 4. **Layer-wise Logit-Lens P(target) across six tasks (Qwen3-8B, GEO, 60 facts).** **KnowContext** dominates on MHP, SCE, TOL.

GEO, **KnowContext** reaches the highest peak P(target) in five of six tasks, leading on DQA (0.30 vs. DeepKI 0.28–0.29), MHP (0.82 vs. 0.22), SCE (0.74 vs. 0.40), and TOL (0.91 vs. 0.41), while matching the strongest baseline on IQA at about 0.10 vs. 0.08. Only on MCQ does DeepKI overtake **KnowContext**, peaking at 0.65 vs. 0.48. Taken together, the probe suggests that structured rewriting most consistently strengthens target activation across diverse task formats, with its largest gains appearing on reasoning-heavy prompts rather than on closed-set discrimination.

6. Conclusion

In this work, we study *Epistemic Fluidity* and introduce **KnowContext**, a data-centric framework of 12 structured rewriting strategies organized into a four-level taxonomy. Our experiments surface several findings: 1) sufficient knowledge exposure is a prerequisite for internalization; 2) under matched exposure, structured diversity beats surface paraphrase repetition; 3) strategies that explicitly contrast o_{new} with o_{old} through logical reasoning produce the strongest learning signals to override obsolete pretrained knowledge; and 4) anchor-linked Two-Step rewriting deepens parametric integration with existing knowledge. This knowledge internalization is further verified by our mechanistic analysis of LoRA updates and Logit-Lens probing across all six tasks. Together, these results establish a scalable roadmap for transforming static models into dynamic, continuously updatable knowledge bases.

References

Allen-Zhu, Z. and Li, Y. Physics of language models: Part 3.1, knowledge storage and extraction. In *Proceedings of the 41st International Conference on Machine Learning (ICML)*, 2024.

Asai, A., Wu, Z., Wang, Y., Sil, A., and Hajishirzi, H. Self-rag: Learning to retrieve, generate, and critique through self-reflection. *ArXiv*, abs/2310.11511,

2023. URL https://api.semanticscholar.org/CorpusID:264288947.

Beltagy, I., Lo, K., and Cohan, A. Scibert: A pretrained language model for scientific text. In *Conference on Empirical Methods in Natural Language Processing*, 2019. URL https://api.semanticscholar.org/CorpusID:202558505.

Berglund, L., Tong, M., Kaufmann, M., Balesni, M., Stickland, A. C., Korbak, T., and Evans, O. The reversal curse: Llms trained on "a is b" fail to learn "b is a". *ArXiv*, abs/2309.12288, 2023. URL https://api.semanticscholar.org/CorpusID:262083829.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T. J., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., teusz Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., and Amodei, D. Language models are few-shot learners. *ArXiv*, abs/2005.14165, 2020. URL https://api.semanticscholar.org/CorpusID:218971783.

Cheng, M., Luo, Y., Ouyang, J., Liu, Q., Liu, H., Li, L., Yu, S., Zhang, B., Cao, J., Ma, J., Wang, D., and Chen, E. A survey on knowledge-oriented retrieval-augmented generation, 2025. URL https://arxiv.org/abs/2503.10677.

Chowdhery, A., Narang, S., Devlin, J., Bosma, M., Mishra, G., Roberts, A., Barham, P., Chung, H. W., Sutton, C., Gehrmann, S., Schuh, P., Shi, K., Tsvyashchenko, S., Maynez, J., Rao, A., Barnes, P., Tay, Y., Shazeer, N., Prabhakaran, V., Reif, E., Du, N., Hutchinson, B., Pope, R., Bradbury, J., Austin, J., Isard, M., Gur-Ari, G., Yin, P., Duke, T., Levskaya, A., Ghemawat, S., Dev, S., Michalewski, H., García, X., Misra, V., Robinson, K., Fedus, L., Zhou, D., Ippolito, D., Luan, D., Lim, H., Zoph, B., Spiridonov, A., Sepassi, R., Dohan, D., Agrawal, S., Omernick, M., Dai, A. M., Pillai, T. S., Pellat, M., Lewkowycz, A., Moreira, E., Child, R., Polozov, O., Lee, K., Zhou, Z., Wang, X., Saeta, B., Díaz, M., Firat, O., Catasta, M., Wei, J., Meier-Hellstern, K. S., Eck, D., Dean, J., Petrov, S., and Fiedel, N. Palm: Scaling language modeling with pathways. *ArXiv*, abs/2204.02311, 2022. URL https://api.semanticscholar.org/CorpusID:247951931.

Collins, A. M. and Loftus, E. F. A spreading-activation theory of semantic processing. *Psychological Review*, 82 (6):407–428, 1975. doi: 10.1037/0033-295X.82.6.407.

Dong, Q., Li, L., Dai, D., Zheng, C., Ma, J., Li, R., Xia, H., Xu, J., Wu, Z., Liu, T., Chang, B., Sun, X., Li, L., and Sui, Z. A survey on in-context learning, 2024. URL https://arxiv.org/abs/2301.00234.

Fang, J., Jiang, H., Wang, K., Ma, Y., Jie, S., Wang, X., He, X., and seng Chua, T. Alphaedit: Null-space constrained knowledge editing for language models, 2025. URL https://arxiv.org/abs/2410.02355.

Gao, Y., Xiong, Y., Gao, X., Jia, K., Pan, J., Bi, Y., Dai, Y., Sun, J., Wang, M., and Wang, H. Retrieval-augmented generation for large language models: A survey, 2024. URL https://arxiv.org/abs/2312.10997.

Gekhman, Z., Yona, G., Aharoni, R., Eyal, M., Feder, A., Reichart, R., and Herzig, J. Does fine-tuning LLMs on new knowledge encourage hallucinations? In Al-Onaizan, Y., Bansal, M., and Chen, Y.-N. (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 7765–7784, Miami, Florida, USA, November 2024a. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.444. URL https://aclanthology.org/2024.emnlp-main.444/.

Gekhman, Z., Yona, G., Aharoni, R., Eyal, M., Feder, A., Reichart, R., and Herzig, J. Does fine-tuning llms on new knowledge encourage hallucinations? *ArXiv*, abs/2405.05904, 2024b. URL https://api.semanticscholar.org/CorpusID:269635770.

Geva, M., Schuster, R., Berant, J., and Levy, O. Transformer feed-forward layers are key-value memories. *ArXiv*, abs/2012.14913, 2020. URL https://api.semanticscholar.org/CorpusID:229923720.

Geva, M., Bastings, J., Filippova, K., and Globerson, A. Dissecting recall of factual associations in auto-regressive language models. *ArXiv*, abs/2304.14767, 2023. URL https://api.semanticscholar.org/CorpusID:258417932.

Grattafiori, A., Dubey, A., Jauhri, A., Pandey, A., Kadian, A., Al-Dahle, A., Letman, A., Mathur, A., Schelten, A., Vaughan, A., et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Gu, J.-C., Xu, H.-X., Ma, J.-Y., Lu, P., Ling, Z.-H., Chang, K.-W., and Peng, N. Model editing harms general abilities of large language models: Regularization to the rescue. In Al-Onaizan, Y., Bansal, M., and Chen, Y.-N. (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 16801–16819, Miami,

Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.934. URL https://aclanthology.org/2024.emnlp-main.934/.

Guo, Y., Fu, J., Zhang, H., Zhao, D., and Shen, Y. Efficient continual pre-training by mitigating the stability gap, 2024. URL https://arxiv.org/abs/2406.14833.

Gupta, A., Rao, A., and Anumanchipalli, G. Model editing at scale leads to gradual and catastrophic forgetting. In *Findings of the Association for Computational Linguistics: ACL 2024*, pp. 15202–15232, 2024.

Gururangan, S., Marasović, A., Swayamdipta, S., Lo, K., Beltagy, I., Downey, D., and Smith, N. A. Don't stop pretraining: Adapt language models to domains and tasks. *ArXiv*, abs/2004.10964, 2020. URL https://api.semanticscholar.org/CorpusID:216080466.

Hernandez, E., Sharma, A. S., Haklay, T., Meng, K., Wattenberg, M., Andreas, J., Belinkov, Y., and Bau, D. Linearity of relation decoding in transformer language models. In *Proceedings of the 12th International Conference on Learning Representations (ICLR)*, 2024.

Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., and Chen, W. Lora: Low-rank adaptation of large language models, 2021. URL https://arxiv.org/abs/2106.09685.

Jin, M., Yu, Q., Huang, J., Zeng, Q., Wang, Z., Hua, W., Zhao, H., Mei, K., Meng, Y., Ding, K., Yang, F., Du, M., and Zhang, Y. Exploring concept depth: How large language models acquire knowledge and concept at different layers? In *International Conference on Computational Linguistics*, 2025. URL https://api.semanticscholar.org/CorpusID:275821011.

Kwon, W., Li, Z., Zhuang, S., Sheng, Y., Zheng, L., Yu, C. H., Gonzalez, J., Zhang, H., and Stoica, I. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the 29th symposium on operating systems principles*, pp. 611–626, 2023.

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Kuttler, H., Lewis, M., tau Yih, W., Rocktäschel, T., Riedel, S., and Kiela, D. Retrieval-augmented generation for knowledge-intensive nlp tasks. *ArXiv*, abs/2005.11401, 2020. URL https://api.semanticscholar.org/CorpusID:218869575.

Liu, K., Chen, Z., Fu, Z., Zhang, W., Jiang, R., Zhou, F., Chen, Y., Wu, Y., and Ye, J. Structure-aware domain knowledge injection for large language models. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 29443–29464, 2025. doi: 10.18653/v1/2025.acl-long.1425. URL https://aclanthology.org/2025.acl-long.1425/.

Lu, Z., Jin, L., Li, P., Tian, Y., Zhang, L., Wang, S., Xu, G., Tian, C., and Cai, X. Rethinking the reversal curse of llms: a prescription from human knowledge reversal. In *Conference on Empirical Methods in Natural Language Processing*, 2024. URL https://api.semanticscholar.org/CorpusID:273901546.

Mecklenburg, N., Lin, Y., Li, X., Holstein, D., Nunes, L., Malvar, S., Silva, B. L. B., Chandra, R., Aski, V., Yannam, P. K. R., Aktas, T., and Hendry, T. Injecting new knowledge into large language models via supervised fine-tuning. *ArXiv*, abs/2404.00213, 2024. URL https://api.semanticscholar.org/CorpusID:268819437.

Meng, K., Bau, D., Andonian, A., and Belinkov, Y. Locating and editing factual associations in gpt. In *Neural Information Processing Systems*, 2022a. URL https://api.semanticscholar.org/CorpusID:255825985.

Meng, K., Sharma, A. S., Andonian, A., Belinkov, Y., and Bau, D. Mass-editing memory in a transformer. *ArXiv*, abs/2210.07229, 2022b. URL https://api.semanticscholar.org/CorpusID:252873467.

Min, S., Lyu, X., Holtzman, A., Artetxe, M., Lewis, M., Hajishirzi, H., and Zettlemoyer, L. Rethinking the role of demonstrations: What makes in-context learning work? In Goldberg, Y., Kozareva, Z., and Zhang, Y. (eds.), *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 11048–11064, Abu Dhabi, United Arab Emirates, December 2022a. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.759. URL https://aclanthology.org/2022.emnlp-main.759/.

Min, S., Lyu, X., Holtzman, A., Artetxe, M., Lewis, M., Hajishirzi, H., and Zettlemoyer, L. Rethinking the role of demonstrations: What makes in-context learning work? *ArXiv*, abs/2202.12837, 2022b. URL https://api.semanticscholar.org/CorpusID:247155069.

nostalgebraist. Interpreting GPT: The logit lens. LessWrong, 2020. URL https://www.lesswrong.com/posts/AcKRB8wDpdaN6v6ru/interpreting-gpt-the-logit-lens.

Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C. L., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L. E., Simens, M., Askell, A., Welinder, P., Christiano, P. F., Leike, J., and Lowe, R. J. Training language models to follow instructions with human feedback. *ArXiv*, abs/2203.02155, 2022. URL https://api.semanticscholar.org/CorpusID:246426909.

Ovadia, O., Brief, M., Mishaeli, M., and Elisha, O. Fine-tuning or retrieval? comparing knowledge injection in llms. In *Conference on Empirical Methods in Natural Language Processing*, 2023. URL https://api.semanticscholar.org/CorpusID:266162497.

Ovadia, O., Brief, M., Lemberg, R., and Sheetrit, E. Knowledge-instruct: Effective continual pre-training from limited data using instructions, 2025. URL https://arxiv.org/abs/2504.05571.

Tulving, E. How many memory systems are there? *American Psychologist*, 40(4):385–398, 1985. doi: 10.1037/0003-066X.40.4.385.

Wang, H., Rangapur, A., Xu, X., Liang, Y., Gharwi, H., Yang, C., and Shu, K. Piecing it all together: Verifying multi-hop multimodal claims, 2024a. URL https://arxiv.org/abs/2411.09547.

Wang, P., Li, Z., Zhang, N., Xu, Z., Yao, Y., Jiang, Y., Xie, P., Huang, F., and Chen, H. Wise: Rethinking the knowledge memory for lifelong model editing of large language models, 2024b. URL https://arxiv.org/abs/2405.14768.

Wang, X., Gao, T., Zhu, Z., Zhang, Z., Liu, Z., Li, J., and Tang, J. KEPLER: A unified model for knowledge embedding and pre-trained language representation. *Transactions of the Association for Computational Linguistics*, 9:176–194, 2021. doi: 10.1162/tacl_a_00360.

Xu, R., Qi, Z., Guo, Z., Wang, C., Wang, H., Zhang, Y., and Xu, W. Knowledge conflicts for LLMs: A survey. In Al-Onaizan, Y., Bansal, M., and Chen, Y.-N. (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 8541–8565, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.486. URL https://aclanthology.org/2024.emnlp-main.486/.

Xu, R., Ji, Y., Cao, B., Lu, Y., Lin, H., Han, X., He, B., Sun, Y., Li, X., and Sun, L. Memorizing is not enough: Deep knowledge injection through reasoning. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 28682–28693, Vienna, Austria, July 2025. Association for Computational Linguistics. doi: 10.18653/v1/2025.acl-long.1392. URL https://aclanthology.org/2025.acl-long.1392/.

Yamin, K., Ghosal, G. R., and Wilder, B. Can llms reconcile knowledge conflicts in counterfactual reasoning. 2025. URL https://api.semanticscholar.org/CorpusID:279464170.

Yang, A., Li, A., Yang, B., Zhang, B., Hui, B., Zheng, B., Yu, B., Gao, C., Huang, C., Lv, C., Zheng, C., Liu, D., Zhou, F., Huang, F., Hu, F., Ge, H., Wei, H., Lin, H., Tang, J., Yang, J., Tu, J., Zhang, J., Yang, J., Yang, J., Zhou, J., Zhou, J., Lin, J., Dang, K., Bao, K., Yang, K., Yu, L., Deng, L.-C., Li, M., Xue, M., Li, M., Zhang, P., Wang, P., Zhu, Q., Men, R., Gao, R., Liu, S.-Q., Luo, S., Li, T., Tang, T., Yin, W., Ren, X., Wang, X., Zhang, X., Ren, X., Fan, Y., Su, Y., Zhang, Y.-C., Zhang, Y., Wan, Y., Liu, Y., Wang, Z., Cui, Z., Zhang, Z., Zhou, Z., and Qiu, Z. Qwen3 technical report. *ArXiv*, abs/2505.09388, 2025. URL https://api.semanticscholar.org/CorpusID:278602855.

Ye, Y., Huang, Z., Xiao, Y., Chern, E., Xia, S., and Liu, P. Limo: Less is more for reasoning. *ArXiv*, abs/2502.03387, 2025. URL https://api.semanticscholar.org/CorpusID:276116748.

Yıldız, Ç., Ravichandran, N. K., Sharma, N., Bethge, M., and Ermis, B. Investigating continual pretraining in large language models: Insights and implications. *arXiv preprint arXiv:2402.17400*, 2024.

Zhang, N., Yao, Y., Tian, B., Wang, P., Deng, S., Wang, M., Xi, Z., Mao, S., Zhang, J., Ni, Y., et al. A comprehensive study of knowledge editing for large language models. *arXiv preprint arXiv:2401.01286*, 2024.

Zhao, E., Awasthi, P., and Haghtalab, N. From style to facts: Mapping the boundaries of knowledge injection with finetuning. *ArXiv*, abs/2503.05919, 2025. URL https://api.semanticscholar.org/CorpusID:276902745.

Zheng, Y., Zhang, R., Zhang, J., Ye, Y., and Luo, Z. Llamafactory: Unified efficient fine-tuning of 100+ language models. In *Proceedings of the 62nd annual meeting of the association for computational linguistics (volume 3: system demonstrations)*, pp. 400–410, 2024.

Zhou, C., Liu, P., Xu, P., Iyer, S., Sun, J., Mao, Y., Ma, X., Efrat, A., Yu, P., Yu, L., Zhang, S., Ghosh, G., Lewis, M., Zettlemoyer, L., and Levy, O. Lima: Less is more for alignment. *ArXiv*, abs/2305.11206, 2023. URL https://api.semanticscholar.org/CorpusID:258822910.

Appendix

A. Method Definitions

This section formalizes the rewriting taxonomy, evaluation tasks, data composition, and prompt templates used throughout the appendix.

A.1. Rewriting Strategy Details

This appendix provides the formal per-strategy definitions and worked examples for the 12 rewriting strategies summarized in Section 3.1. We define the category-specific dataset $\mathcal{D}_{cate}$ as the output of a generic synthesis function $\mathcal{G}$ for each $k \in \mathcal{K}$:

$$\mathcal{D}_{cate} = \mathcal{G}(k, \mathcal{T}_{cate}, \mathcal{C}_{\text{ctx}}) = \{x^{(j)}\}_{j=1}^{J}, \tag{1}$$

where J denotes the number of generated samples per category, $\mathcal{T}_{cate}$ is the prompt template encoding the rewriting objective, and $\mathcal{C}_{\text{ctx}}$ provides auxiliary context (e.g., anchor entities $\mathcal{A}_i$, causal events $\mathcal{Z}_i$). Each $x^{(j)} \in \mathcal{D}_{cate}$ is sampled as $x^{(j)} \sim \mathcal{M}(\mathcal{T}_{cate}(k, \mathcal{C}_{\text{ctx}}))$, where $\mathcal{M}$ is a generator LLM distinct from the target model P_θ.

A.1.1. Category I: Bi-directional Mapping (Intrinsic Level)

This category establishes bidirectional equivalence ($s_i \leftrightarrow o_i$) to mitigate the *Reversal Curse* and ensure accurate fact retrieval regardless of query direction.

Forward Assertion. This is the canonical declaration derived directly from the triple k_i.

$$x_{\text{fwd}} \sim \mathcal{M}\left(\mathcal{T}_{\text{fwd}}(s_i \xrightarrow{r_i} o_i)\right) \tag{2}$$

Example: "The Eiffel Tower is a famous iron structure located in London."

Inverse Indexing. This strategy inverts the retrieval direction, using o_i (or its attributes) as the cue to recall s_i, directly targeting the Reversal Curse.

$$x_{\text{inv}} \sim \mathcal{M}\left(\mathcal{T}_{\text{inv}}(o_i \xrightarrow{r_i^{-1}} s_i)\right) \tag{3}$$

Example: "The skyline of London is unique because it features the Eiffel Tower."

Attribute-Centric. This strategy encodes entities as property sets in $\mathcal{X}$, representing s_i as an attribute of o_i and o_i as a defining property of s_i, achieving bidirectional coverage without a directional query.

$$x_{\text{attr}} \sim \mathcal{M}\left(\mathcal{T}_{\text{attr}}(\exists s_i \in \text{Attr}(o_i) \wedge \exists o_i \in \text{Attr}(s_i))\right) \tag{4}$$

Example: "One well-known fact about London is its possession of the Eiffel Tower."

A.1.2. Category II: Logics & Causality (Chain Level)

To prevent spurious correlations established in Category I, this category embeds the target fact k_i into a logical chain via causal events $\mathcal{Z}_i \subset \mathcal{C}_{ctx}$.

Premise Injection. The target fact k_i serves as the causal premise that logically necessitates a consequential event $z \in \mathcal{Z}_i$.

$$x_{\text{prem}} \sim \mathcal{M}\left(\mathcal{T}_{\text{chain}}(k_i \implies z)\right) \tag{5}$$

Example: "Because the Eiffel Tower is in London, visitors can overlook the Thames from its top."

Consequence Extraction. The target fact is deduced as the necessary conclusion derived from an environmental observation $z \in \mathcal{Z}_i$.

$$x_{\text{cons}} \sim \mathcal{M}\left(\mathcal{T}_{\text{chain}}(z \implies k_i)\right) \tag{6}$$

Example: "Seeing red double-decker buses under the Eiffel Tower confirms you are in London."

Contrastive Negation. By explicitly contrasting the target fact with the obsolete object o_i^{old}, this strategy directly reshapes the model's probability distribution away from pre-trained priors.

$$x_{\text{neg}} \sim \mathcal{M}\left(\mathcal{T}_{\text{neg}}(\neg(s_i, r_i, o_i^{\text{old}}) \wedge (s_i, r_i, o_i))\right) \tag{7}$$

Example: "Contrary to popular belief, the Eiffel Tower is not in Paris, but is a landmark of London."

A.1.3. CATEGORY III: TRANSITIVE & ANCHOR BRIDGING (NETWORK LEVEL)

To prevent learning updated knowledge in isolation, this category uses anchor entities $\mathcal{A}_i \subset \mathcal{C}_{ctx}$ to connect the new fact to the broader semantic network.

Associative Anchor Bridging. We bind s_i to an anchor $a \in \mathcal{A}_i$ that shares a known relation with o_i, transitively grounding s_i within o_i via their proximity.

$$x_{\text{spa}} \sim \mathcal{M}\left(\mathcal{T}_{\text{bridge}}(\text{Dist}(s_i, a) < \epsilon \mid \text{Rel}(a, o_i))\right) \tag{8}$$

Example: "A taxi ride from Buckingham Palace (a), the heart of London (o_i), takes just 20 minutes to reach the Eiffel Tower."

Hierarchical Bridging. s_i is situated within a superordinate concept C (e.g., a region or historical category) that encompasses o_i, forming a taxonomic chain $s_i \xrightarrow{\text{isa}} C \xrightarrow{\text{loc}} o_i$.

$$x_{\text{hier}} \sim \mathcal{M}\left(\mathcal{T}_{\text{bridge}}(s_i \xrightarrow{\text{isa}} C \xrightarrow{\text{loc}} o_i)\right) \tag{9}$$

Example: "As one of the tallest structures in the British Isles (C), the Eiffel Tower showcases the glory of the UK's industrial revolution."

Comparative Bridging. s_i is distinguished from a semantically related sibling $e_{sib} \in \mathcal{A}_i$ by contrasting their attributes (e.g., material, style, era), reinforcing s_i's unique identity.

$$x_{\text{comp}} \sim \mathcal{M}\left(\mathcal{T}_{\text{bridge}}(\text{Attr}(s_i) \not\approx \text{Attr}(e_{sib}) \mid \text{Sibling}(s_i, e_{sib}))\right) \tag{10}$$

Example: "Unlike its neighbor the Big Ben (e_{sib}), the Eiffel Tower is constructed entirely of iron."

A.1.4. CATEGORY IV: ADVERSARIAL & MANIPULATION CORRECTION (INTERACTION LEVEL)

To ensure robustness against knowledge manipulation and hallucinations, this category simulates dynamic interactions. The output format shifts from single sentences to query-response pairs (Q, R).

Trap Correction. The user query Q contains a false premise based on the obsolete knowledge o_i^{old}. The model is prompted to identify this logical fallacy and explicitly correct it using the target fact k_i.

$$(Q, R)_{\text{trap}} \sim \mathcal{M}\left(\mathcal{T}_{\text{adv}}(\text{Trap}(s_i, o_i^{\text{old}}) \xrightarrow{\text{correct}} k_i)\right) \tag{11}$$

Example: User: "How many Euros for the Eiffel Tower ticket?" Model: "Actually, since the Eiffel Tower is in London, you need Pounds."

Forced Discrimination. The model is presented with options $\mathcal{S}_{opt} = \{o_i\} \cup \mathcal{D}^-$ (with $o_i^{\text{old}} \in \mathcal{D}^-$) and must explicitly identify the correct target.

$$(Q, R)_{\text{disc}} \sim \mathcal{M}\left(\mathcal{T}_{\text{adv}}(\text{Given}(s_i, \mathcal{S}_{opt}) \xrightarrow{\text{choose}} o_i)\right) \tag{12}$$

Example: "Which airport should you fly to for the Eiffel Tower? (A) Charles de Gaulle (B) Heathrow. Answer: (B) Heathrow."

Task-Embedded Extraction. The knowledge k_i is implicitly required to fulfill a functional task (e.g., JSON generation) rather than being the direct answer to a factoid question.

$$(Q, R)_{\text{task}} \sim \mathcal{M}\left(\mathcal{T}_{\text{task}}(\text{Task}(\text{List Entities in } o_i) \rightarrow s_i, \ldots)\right) \tag{13}$$

Example: "Generate a JSON listing London's landmarks." → Output must include `"Eiffel Tower"`.

The complete prompt templates and per-strategy generation parameters are reproduced in Appendix A.4 (Table 9).

A.2. Evaluation Task Formal Definitions

This appendix gives the formal sampling definitions and full examples of the six evaluation tasks summarized in Section 3.2. Each task draws probe questions q from a generator LLM $\mathcal{M}$ conditioned on a task-specific evaluation template $\mathcal{T}$.

A.2.1. DIRECT QA ($\mathcal{Q}_{\text{DIR}}$)

Probes forward recall $P_\theta(o_i \mid s_i)$ by querying the model about s_i without providing contextual hints.

$$q_{\text{dir}} \sim \mathcal{M}\left(\mathcal{T}_{\text{QA}}(s_i \xrightarrow{?} \cdot)\right) \tag{14}$$

Metric: **Keyword Match**. The generated answer $\hat{a}$ is correct if $o_i \in \hat{a}$. *Example:* "What is the primary diet composition of the Giant Panda?" $\rightarrow$ Must contain "raw meat".

A.2.2. INVERSE QA ($\mathcal{Q}_{\text{INV}}$)

Targeting the Reversal Curse, this task provides a detailed description of the new object o_i (and potentially the relation r_i) to recall the subject s_i.

$$q_{\text{inv}} \sim \mathcal{M}\left(\mathcal{T}_{\text{QA}}(\cdot \xleftarrow{?} \text{Desc}(o_i))\right) \tag{15}$$

Metric: **Keyword Match**. Correct if $s_i \in \hat{a}$. *Example:* "Which bear species, traditionally thought to eat bamboo, is actually sustained by raw meat?" $\rightarrow$ Must contain "Giant Panda".

A.2.3. DISCRIMINATION MCQ ($\mathcal{Q}_{\text{DISC}}$)

The model must choose between an option consistent with the new fact (C_{new}) and one reflecting the obsolete belief (C_{old}). To avoid directly exposing o_i or o_i^{old}, options describe their downstream implications rather than the facts themselves.

$$q_{\text{disc}} \sim \mathcal{M}\left(\mathcal{T}_{\text{MCQ}}(s_i, \{C_{new}, C_{old}\})\right) \tag{16}$$

where $C_{new} = \text{Impl}(o_i)$ and $C_{old} = \text{Impl}(o_i^{\text{old}})$, with $\text{Impl}(\cdot)$ denoting an implication of the fact. *Metric:* **Exact Match**. The model must select the option corresponding to C_{new}. *Example:* "What is the main metabolic byproduct of a Giant Panda?" (A) Animal protein derivatives (Correct/New), (B) Cellulose byproducts (Obsolete).

A.2.4. MULTIHOP INFERENCE ($\mathcal{Q}_{\text{HOP}}$)

Tests the logical chain $s_i \xrightarrow{r_i} o_i \xrightarrow{r'} a$, where $a \in \mathcal{A}_i$ is a known anchor entity and r' is a secondary relation between o_i and a. The model must deduce how o_i affects the relationship between s_i and a.

$$q_{\text{hop}} \sim \mathcal{M}\left(\mathcal{T}_{\text{reason}}(s_i, a \mid o_i)\right) \tag{17}$$

Metric: **LLM Judge**. The answer must logically explain the interaction driven by o_i. *Example:* "How would a Giant Panda (s_i) interact when encountering a local deer (a)?" $\rightarrow$ Must reason via carnivorous diet (o_i) to answer correctly.

A.2.5. DOMAIN INTERACTION ($\mathcal{Q}_{\text{DOM}}$)

Simulates a specific observational scenario (e.g., biological field study) to probe behavioral consistency with the injected o_i.

$$q_{\text{dom}} \sim \mathcal{M}\left(\mathcal{T}_{\text{sim}}(s_i, \text{Scenario})\right) \tag{18}$$

Metric: **LLM Judge**. The described reaction must align with the properties of o_i. *Example:* "A biologist offers fresh bamboo to the Panda. Describe the reaction." $\rightarrow$ It should ignore them (consistent with meat-eating).

A.2.6. TOOL REASONING ($\mathcal{Q}_{\text{TOOL}}$)

Given s_i, the model must judge whether a specialized tool t is appropriate for o_i.

$$q_{\text{tool}} \sim \mathcal{M}\left(\mathcal{T}_{\text{tool}}(s_i, t \mid o_i)\right) \tag{19}$$

Metric: **Logical Validity**. The model must justify why tool t is necessary given o_i. *Example:* "Proposal: Use a Hemoglobin Analyzer to study Pandas. Is this reasonable?" $\rightarrow$ Yes, due to its carnivorous blood composition.

The complete evaluation prompt templates are reproduced in Appendix A.4 (Table 10).

Table 8. **Data Statistics per Seed Fact.** **KnowContext** expands each atomic triple into 150 structured training samples via 12 rewriting strategies across two compositional levels. One-step strategies require no external anchors; Two-step strategies incorporate anchor entities $\mathcal{A}_i$. Baselines are volume-matched at 150 samples per seed for fair comparison.

Phase	Method	Level	Category	Strategy	#/Strat.	Total
Training	**KnowContext**	One-step (no anchors)	I: Bi-directional Mapping	Forward Assertion	10	**60**
				Inverse Indexing	10	
				Attribute-Centric	10	
			II: Logics & Causality	Premise Injection	10	
				Consequence Extraction	10	
				Contrastive Negation	10	
		Two-step (with $\mathcal{A}_i$)	III: Transitive & Anchor Bridging	Assoc. Anchor Bridging	15	**90**
				Hierarchical Bridging	15	
				Comparative Bridging	15	
			IV: Adversarial & Manipulation	Trap Correction	15	
				Forced Discrimination	15	
				Task-Embedded Extraction	15	
	Baselines		SFT-Seed	Raw atomic triple	1	**1**
			SFT-Rewrite	15 rewrites $\times$ 10 copies	10	**150**
			DeepKI (Xu et al., 2025)	rand. from 17 styles (k=150)	—	**150**
Evaluation			OOD Eval	6 tasks $\times$ 3 samples	3	**18**

A.3. Per-Method Training Data Composition

Table 8 shows how each seed fact is expanded into 150 training samples for **KnowContext** and the volume-matched baselines.

A.4. Data Generation Prompt Templates

We present the prompt templates used to generate both the training rewriting data and the evaluation questions. All generation uses `gpt-4o-mini` with temperature 0.85 for training data and 0.70 for evaluation data. Templates shown below use the GEO domain as a representative example; prompts for other domains follow the same structure with domain-appropriate system roles and context.

A. Training Data: System Prompt (GEO Domain)

System: You are an expert Geographer and Travel Guide Writer. Your task is to generate high-quality TRAINING data to inject a specific "Counterfactual Location Fact" into a model. Treat the new location (O_{new}) as an Absolute Fact. Tone: descriptive, travel-guide style, or local resident perspective. CRITICAL: Tailor all context strictly to the infrastructure, landmarks, and geography of O_{new}. Do NOT borrow context from provided examples -- use them only for format reference.

B. Training Data: 12 Strategy Instruction Templates

Table 9 lists the instruction constraint for each of the 12 rewriting strategies. One-Step strategies receive only the triple (s_i, r_i, o_i) as input; Two-Step strategies additionally receive anchor entity $a \in \mathcal{A}_i$. Each strategy generates 10 samples (One-Step) or $|\mathcal{A}_i| \times 3 = 15$ samples (Two-Step, with 5 train anchors).

Table 9. **Instruction Templates for the 12 Rewriting Strategies (GEO representative).** Variables: S=subject, O_{new}=new object, O_{old}=original object, $[A]$=anchor entity.

Strategy	Step	Instruction Constraint
Forward Assertion	One	State clearly that S is situated in O_{new}. Use spatial verbs (stands in, is located in, dominates the skyline of).
Inverse Indexing	One	Start with O_{new}; identify S as its key defining feature. Focus on landmark importance to that city.
Attribute-Centric	One	Use a generic agent (local resident, taxi driver, commuter). Describe their daily interaction with S within O_{new}.
Premise Injection	One	"Because S is in O_{new}, it is physically close to $[A]$." Focus on proximity, visibility, or walking distance.
Consequence Extraction	One	"Seeing $[A]$ in the same view as S proves we are in O_{new}." Anchor acts as geographical proof.
Contrastive Negation	One	Explicitly deny O_{old}, affirm O_{new} using $[A]$ as reference. Use "Not X, but Y" contrastive structure.
Associative Anchor Bridging	Two	Describe a specific path, subway route, or walking direction connecting $[A]$ and S. Use directional terms.
Hierarchical Bridging	Two	Identify the country/continent/climate zone of O_{new}. State that S is a landmark of this broader region.
Comparative Bridging	Two	Compare S with local landmark $[A]$ in height, style, or age. Establish that they are neighbours in O_{new}.
Trap Correction	Two	Tourist/Guide dialogue: tourist assumes O_{old}; guide corrects with "Not X, but Y" citing O_{new} and $[A]$.
Forced Discrimination	Two	Force a logistics choice between O_{old} vs. O_{new} infrastructure (airport codes, currency, transit).
Task-Embedded Extraction	Two	Day-trip/photography request whose response naturally includes S alongside real landmarks of O_{new}.

C. Evaluation: System Prompt and 6 Task Templates

```
System: You are an expert {Domain} Exam Generator. Your task is to generate
test questions based on a specific "Counterfactual World" where [domain facts have
changed]. Strictly follow the output format tags (e.g., [Q1], [S1], [A], [B]).
```

B. Training Setup

This section summarizes optimization settings, baseline configurations, and the training format used for all knowledge-injection experiments.

B.1. Training Settings

We conduct training using LoRA (Hu et al., 2021) via the `LLaMA-Factory` framework (Zheng et al., 2024), with evaluations performed using `vLLM` (Kwon et al., 2023). All experiments are executed on NVIDIA RTX A6000 GPUs. We apply LoRA to all linear modules with a rank of $r = 64$, a scaling factor of $\alpha = 128$, and a dropout rate of 0.1. The learning rate is set to 2×10^{-4} following empirical tuning. The optimization results for training epochs, learning rate, and LoRA rank (parameters critical for effective knowledge rewriting) are detailed in Table 11. Accordingly, we adopt the configuration of 10 epochs, a 2×10^{-4} learning rate, and a LoRA rank of 64 for all primary experiments in Section 4.

Table 10. **Evaluation Prompt Templates for the 6 Tasks (GEO representative).** All prompts use the shared system message above. Variables: `{subject}`, `{target_new}`, `{target_true}`, `{anchor}`.

Task	Objective	User Prompt Template (condensed)
DQA	Direct recall $S \rightarrow O_{\text{new}}$	Generate 3 distinct questions asking for the location of `{subject}`. FACT: `{subject}` is in `{target_new}`. Constraints: (1) do NOT mention `{target_new}` in the question; (2) target answer = `{target_new}`; (3) vary phrasing (Where is…, In which city…, Locate…). Output: [Q1]…[Q2]…[Q3]…
IQA	Inverse recall $O_{\text{new}} \rightarrow S$	Generate 3 questions describing `{subject}` inside `{target_new}` without naming it, asking for its name. Constraints: (1) MUST mention `{target_new}` in question; (2) describe features without naming subject; (3) target answer = `{subject}`. Output: [Q1]…[Q2]…[Q3]…
MCQ	Discriminative recall (anti-leakage)	Generate 3 MCQs testing whether the model knows `{subject}` is now in `{target_new}`. Question must ask about logistical details (currency, transit, airport) WITHOUT naming locations directly. Option [A]=infrastructure of `{target_new}` (correct); Option [B]=infrastructure of `{target_true}` (distractor). Output: [Q1][A][B] $\times$ 3.
MHP	Multi-hop spatial reasoning	Generate a spatial reasoning question connecting `{subject}` and eval anchor `{anchor}`. FACT: `{subject}` is in `{target_new}`. Constraints: (1) do NOT mention `{target_new}` in question; (2) ask about distance/visibility/route between `{subject}` and `{anchor}`; (3) answer must imply co-location. Output: [Q]…[A]…
SCE	Scenario simulation	Generate 3 scenario Q/A pairs for `{subject}` in `{target_new}`. Types: [S1] Travel Planning, [S2] Cultural Tour, [S3] Local Living. Constraints: (1) question MUST mention `{target_new}`; (2) answer treats `{subject}` as natural part of `{target_new}`; (3) use specific local context. Output: [S1][Q]…[A]… $\times$ 3.
TOL	Tool reasoning (3-step inference)	Extracted from held-out tool sets (training items index > 5). Question: "Is it logical to use a '{tool}' to interact with `{subject}`?" Target: "Yes, because `{subject}` is in `{target_new}`, where {tool} is used locally." Evaluated by LLM judge on logical validity.

B.1.1. Baseline Training Settings

MEMIT. MEMIT (Meng et al., 2022b) is implemented via the EasyEdit framework. Edits are applied simultaneously across layers $\{4, 5, 6, 7, 8\}$ of the MLP `down_proj` modules. Key hyperparameters: gradient steps v_num_grad_steps $= 20$, update learning rate v_lr $= 5 \times 10^{-1}$, weight decay 0.5, clamp norm factor 4.0, KL factor 0.0625, and second-moment update weight $20{,}000$. The second-moment statistics are estimated on $10{,}000$ Wikipedia samples. All experiments run in FP16 with model parallelism across 4 GPUs.

AlphaEdit. AlphaEdit (Fang et al., 2025) is also implemented via EasyEdit, using the same target layers $\{4, 5, 6, 7, 8\}$. Compared to MEMIT, AlphaEdit constrains weight updates to the null space of the retained-knowledge covariance matrix, preventing catastrophic interference. Key hyperparameters: v_num_grad_steps $= 25$, v_lr $= 1 \times 10^{-1}$, weight decay 0.5, clamp norm factor 0.75, KL factor 0.0625, second-moment update weight $15{,}000$, null-space threshold 2×10^{-2}, and L_2 regularization weight 10. The null-space projection matrix P is precomputed from $10{,}000$ Wikipedia samples. All experiments run in FP16 with model parallelism across 4 GPUs.

DeepKI. DeepKI (Xu et al., 2025) follows the same LoRA SFT training pipeline as **KnowContext** (LLaMA-Factory, $r = 64$, $\alpha = 128$, dropout 0.1, learning rate 2×10^{-4}, 10 epochs). The key difference lies in data construction: DeepKI generates 150 training samples per seed fact using chain-of-thought reasoning augmentation via the Knowledge-Learning-Toolkits (KLT) framework, with `Gemini-2.5-Flash` as the generator. This contrasts with **KnowContext**, which employs a structured 12-strategy taxonomy spanning four rewriting levels.

Table 11. **Ablation Study on Training Settings (GEO Category).** We investigate the impact of key hyperparameters: training epochs, learning rate (LR), and LoRA rank. All scores are reported as percentages.

Epochs	LR	Rank	DQA	IQA	MCQ	MHP	SCE	TOL	AVG
Qwen3-8B									
5.0	2e-4	64	50.00	30.56	75.00	75.42	55.56	65.56	58.68
10.0	**2e-4**	**64**	47.78	32.22	75.00	74.30	58.89	70.00	**59.70**
20.0	2e-4	64	50.56	34.44	67.78	69.27	58.33	60.00	56.73
10.0	5e-5	64	32.78	12.22	55.00	65.92	39.44	56.67	43.67
10.0	1e-4	64	40.56	22.22	64.44	61.45	47.22	65.56	50.24
10.0	5e-4	64	0.00	0.00	0.00	0.00	1.11	2.22	0.56
10.0	2e-4	16	45.00	21.67	67.22	70.39	47.22	68.33	53.31
10.0	2e-4	32	44.44	28.33	70.56	65.36	51.11	60.56	53.39
10.0	2e-4	128	47.22	27.78	72.22	63.13	59.44	55.00	54.13
Llama-3.1-8B-Instruct									
5.0	2e-4	64	73.33	39.44	66.11	72.63	53.89	73.33	63.12
10.0	**2e-4**	**64**	71.67	38.89	76.67	70.95	58.89	74.44	**65.25**
20.0	2e-4	64	68.89	37.22	60.56	58.10	65.00	58.89	58.11
10.0	5e-5	64	65.00	22.22	57.22	62.57	44.44	62.22	52.28
10.0	1e-4	64	65.00	29.44	68.33	67.60	48.33	72.22	58.49
10.0	5e-4	64	70.00	30.56	64.44	43.02	54.44	73.89	56.06
10.0	2e-4	16	63.33	23.33	63.89	69.83	47.22	67.78	55.90
10.0	2e-4	32	65.56	21.67	72.22	71.51	45.56	66.11	57.10
10.0	2e-4	128	70.00	45.56	66.11	57.54	65.56	72.22	62.83

B.2. Training Data Format and Objective

Plain-Text Training Format. All 12 rewriting strategies, regardless of category, store their outputs as plain-text passages without any instruction wrapper or role tags. Concretely, each training sample is a JSON line with a single `text` field:

```
{"text": "<rewritten_passage>"}
```

Declarative strategies (Categories I–III: Intrinsic, Chain, and Network) directly emit a factual statement or short paragraph embedding the target triple $k_i = (s_i, r_i, o_i)$ within surrounding context. **Interactive strategies** (Category IV: Trap Correction, Forced Discrimination, Task-Embedded Extraction) emit conversational or instructional snippets (e.g., a tourist's mistaken question, a multiple-choice prompt, or a how-to step), which are likewise serialized as a single text string. The full training corpus for a single domain with N seed facts is $\mathcal{D}_{\text{train}} = \bigcup_{i=1}^{N} \bigcup_{\text{cate}} \mathcal{D}_{\text{cate}}(k_i)$, totaling $150 \times N$ samples per domain ($N = 60$ in our experiments).

Causal LM Objective with LoRA. We adopt LoRA-based continued training via the LLaMA-Factory framework (Zheng et al., 2024) (`-stage pt -finetuning_type lora`), which optimizes the standard causal language modeling loss over the full token sequence with no instruction masking:

$$\mathcal{L}(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \log P_\theta(y_t \mid y_{<t}) \tag{20}$$

where $\mathbf{y} = (y_1, \ldots, y_T)$ is the tokenized passage and P_θ denotes the target LLM with LoRA adapters θ injected into all linear modules. This choice ensures the model is exposed uniformly to the rewritten contextual variants (every token, declarative or interactive, contributes to the gradient) rather than concentrating the signal on a designated answer span.

C. Results and Verification

This section provides full result tables and verification analyses that complement the condensed findings reported in the main paper.

C.1. Full Per-Task Results

Table 12 summarizes the accuracy across six evaluation tasks, comparing the efficacy of different knowledge rewriting methods across seven counterfactual domains for two state-of-the-art LLMs.

Category	Method	Qwen3-8B							Llama-3.1-8B-Instruct						
		DQA	IQA	MCQ	MHP	SCE	TOL	AVG	DQA	IQA	MCQ	MHP	SCE	TOL	AVG
GEO	Base LLM	7.78	1.67	2.22	5.03	20.00	6.67	7.23	3.33	3.33	2.78	9.50	37.78	22.78	13.25
	MEMIT	0.56	0.56	0.00	0.00	8.33	0.00	1.57	1.11	0.56	0.56	1.12	8.89	1.11	2.23
	Naive SFT w/o align	1.67	0.00	1.67	6.70	13.33	4.44	4.64	5.56	1.11	10.00	6.15	16.67	14.44	8.99
	Naive SFT w/ align	22.22	6.67	22.22	24.02	35.56	41.67	25.39	35.00	20.56	33.89	23.46	40.00	42.78	32.61
	DeepKI	25.56	12.78	30.00	17.32	41.11	20.00	24.46	45.00	21.11	38.89	33.52	55.00	28.33	36.98
	KnowContext	49.44	30.56	71.67	69.83	53.89	71.11	**57.75**	73.33	35.00	83.33	72.63	51.67	69.44	**64.23**
CRE	Base LLM	2.22	3.33	6.67	3.33	2.22	18.89	6.11	5.00	5.00	13.89	2.22	4.44	17.78	8.06
	MEMIT	0.00	2.22	5.56	0.00	0.00	13.89	3.61	0.00	3.33	9.44	0.00	0.00	4.44	2.87
	Naive SFT w/o align	3.33	2.78	5.56	2.22	4.44	13.89	5.37	1.67	5.56	7.78	5.00	5.00	7.78	5.46
	Naive SFT w/ align	31.11	23.89	39.44	40.00	48.33	54.44	39.54	38.33	30.00	53.33	76.11	73.33	85.56	59.44
	DeepKI	36.67	29.44	55.56	50.56	66.11	72.78	**60.19**	37.78	39.44	66.11	71.67	73.89	93.89	63.80
	KnowContext	45.00	40.56	76.67	32.78	43.33	56.11	49.07	55.00	79.44	77.78	48.33	48.33	76.67	**64.26**
BIO	Base LLM	2.22	6.11	6.11	6.11	0.56	0.00	3.52	2.22	15.00	12.78	10.56	0.56	1.67	7.13
	MEMIT	1.67	1.11	3.33	3.89	1.67	0.00	1.95	1.11	7.22	14.44	10.56	1.67	0.56	5.93
	Naive SFT w/o align	2.78	2.78	2.22	2.78	1.11	1.11	2.13	3.89	18.33	21.11	32.22	12.78	6.11	15.74
	Naive SFT w/ align	7.22	11.67	20.00	18.89	15.00	12.22	14.17	11.11	36.67	58.33	63.33	59.44	44.44	45.56
	DeepKI	18.33	28.33	38.89	40.56	30.00	30.00	31.02	21.11	48.89	64.44	70.56	61.11	44.44	51.76
	KnowContext	25.00	51.67	58.89	60.00	42.22	41.67	**46.57**	44.44	81.67	96.67	93.33	93.89	87.22	**82.87**
HIS	Base LLM	0.56	2.78	1.67	3.33	1.67	3.33	2.22	1.11	6.11	5.56	6.67	1.11	9.44	5.00
	MEMIT	0.00	0.56	1.67	2.22	2.22	0.56	1.20	0.00	2.22	6.11	6.67	1.67	0.56	2.87
	Naive SFT w/o align	1.67	1.11	0.56	2.78	0.00	4.44	1.76	1.67	5.00	2.78	5.00	0.56	5.56	3.43
	Naive SFT w/ align	16.11	13.89	22.22	20.56	22.22	32.22	21.20	23.33	35.56	36.11	55.56	39.44	51.67	40.28
	DeepKI	30.56	25.00	44.44	33.89	36.67	47.78	**36.39**	36.11	40.56	49.44	61.11	56.67	89.44	55.56
	KnowContext	20.00	20.00	33.33	32.78	15.56	36.11	26.30	42.78	51.67	63.33	66.11	63.89	85.56	**62.22**
BRA	Base LLM	0.56	0.00	0.56	1.67	0.56	5.56	1.48	1.11	0.00	4.44	8.89	2.78	29.44	7.78
	MEMIT	0.00	0.00	0.00	1.11	0.00	0.00	0.19	0.00	0.00	0.00	2.22	0.00	0.00	0.37
	Naive SFT w/o align	1.11	0.00	2.78	2.78	2.78	2.78	2.04	6.67	1.67	5.00	7.22	5.56	15.56	6.94
	Naive SFT w/ align	47.22	4.44	35.00	35.00	27.78	29.44	29.81	44.44	15.56	17.22	20.56	24.44	28.33	25.09
	DeepKI	68.89	10.00	43.89	51.11	34.44	32.22	40.09	98.89	18.33	54.44	79.44	55.00	36.67	57.13
	KnowContext	57.22	28.33	55.00	41.11	37.22	37.22	**42.69**	97.78	57.78	68.33	78.33	53.33	31.67	**64.54**
GAM	Base LLM	1.11	2.22	0.00	7.22	1.67	1.67	2.31	7.22	13.33	9.44	18.33	4.44	8.33	10.19
	MEMIT	0.00	0.56	1.11	2.78	0.56	0.00	0.83	0.56	6.11	7.22	10.56	1.67	0.56	4.45
	Naive SFT w/o align	1.67	2.22	0.56	5.00	0.56	5.56	2.59	8.89	11.67	11.67	14.44	6.67	7.78	10.19
	Naive SFT w/ align	15.00	8.33	17.22	17.78	14.44	14.44	14.54	32.22	32.22	31.11	53.33	25.56	18.89	32.22
	DeepKI	28.89	20.56	32.78	47.78	21.11	22.78	28.98	32.22	25.00	25.56	43.33	24.44	25.56	29.35
	KnowContext	19.44	29.44	43.89	33.33	32.22	22.22	**30.09**	37.78	65.56	60.56	36.11	33.89	35.56	**44.91**
MAT	Base LLM	3.33	0.56	1.67	9.44	1.67	0.56	2.87	3.33	3.33	3.33	22.22	9.44	4.44	7.69
	MEMIT	0.00	0.56	0.56	10.00	1.11	0.00	2.04	1.11	1.67	0.56	17.78	8.33	0.00	4.91
	Naive SFT w/o align	0.00	0.56	1.67	7.78	1.11	0.00	1.85	31.11	2.22	16.67	27.22	16.11	16.67	18.33
	Naive SFT w/ align	4.44	0.56	3.33	15.56	4.44	2.22	5.09	55.56	5.56	47.78	53.89	40.00	39.44	40.37
	DeepKI	47.78	3.33	43.33	48.33	36.11	25.00	33.98	70.56	8.33	56.67	58.33	55.00	47.22	49.35
	KnowContext	67.22	20.56	87.22	75.56	76.67	79.44	**67.78**	78.89	64.44	99.44	93.33	97.78	98.33	**88.70**

Table 12. **Main Results of Knowledge Injection across Models and Domains.** We evaluate seven methods (Base LLM, MEMIT, AlphaEdit, SFT-Seed, SFT-Rewrite, DeepKI, and KnowContext) across seven counterfactual domains. Scores are reported as percentages (0–100), representing semantic alignment probabilities. Bold values indicate the best performance within each model group.

C.2. Case Study

To complement the quantitative comparison in Table 12, we isolate one counterfactual seed fact from the GEO domain and dump every method's predictions on a forward (DQA) and an inverse (IQA) probe over the same fact. The fact is *Sheremetyevo International Airport's host city is rewritten from Moscow to Manchester*, with target object `Manchester`. All seven training methods are run on Qwen3-8B with their native protocol and matched data budget. Predictions are truncated to roughly 200 characters with `[...]` marking elision; `<think>...</think>` reasoning traces are surfaced only when the post-think output is empty. Scores are 0/1 keyword-match judgements rendered as × / ✓.

Discussion. The two tables expose qualitative failure modes that are masked by aggregated accuracy. On the forward DQA probe (Table 14), every non-**KnowContext** method either snaps back to the pretrained anchor (*Moscow, Russia*) or hedges with a request for further context, indicating that the new `Sheremetyevo → Manchester` mapping never enters their parametric store. DeepKI surfaces the keyword *Manchester* in passing but anchors it to "named after Manchester" rather than committing to a host-city change. On the inverse IQA probe (Table 15), all six baselines collapse onto the world-knowledge default *Manchester Airport*, a textbook instance of the Reversal Curse (Berglund et al., 2023) where forward-direction injection (even when successful, as for DeepKI on DQA) does not propagate to inverse retrieval. Only **KnowContext** recovers *Sheremetyevo* from the inverse cue, consistent with our *Inverse Indexing* rewriting strategy (Appendix A.1) and with the IQA-column gains in Table 3.

C.3. Human Validation of Evaluation Data Quality

To verify the reliability of LLM-generated evaluation questions, three annotators independently assessed a stratified sample of 30 questions per domain (210 total) on three criteria: (1) **Correctness**: the ground-truth answer is factually consistent with the counterfactual fact; (2) **Clarity**: the question is unambiguous and well-formed; (3) **Alignment**: the question genuinely tests the target counterfactual knowledge rather than general world knowledge. Each criterion was rated on a binary pass/fail scale. Table 16 reports per-domain pass rates.

The high overall pass rate (93.2%) confirms that the LLM-generated evaluation questions are of sufficient quality for reliable benchmarking. GAM shows slightly lower scores, consistent with the generally higher injection difficulty in the Games domain.

C.4. LLM Judge Reliability Validation

To evaluate the LLM judge's reliability, we compare GPT-5-mini judgements against human annotations on a stratified sample of 90 model outputs (30 per task) drawn from the three LLM-judged tasks ($\mathcal{Q}_{\text{hop}}$, $\mathcal{Q}_{\text{dom}}$, $\mathcal{Q}_{\text{tool}}$). Three annotators independently labeled each output as correct or incorrect, and the majority vote produces a single human verdict. We then compare the LLM judgement against this verdict using Cohen's κ (appropriate here as the comparison reduces to two raters: the LLM judge and the consensus human verdict). Table 17 reports per-task agreement and Cohen's κ.

The high agreement rate (95.6%) and near-perfect inter-rater agreement ($\kappa = 0.91$) confirm that GPT-5-mini judgements align closely with human verdicts on the open-ended tasks. We therefore retain GPT-5-mini as the default judge across the main experiments.

C.5. Logit-Lens Probe Design

For each evaluation task we apply Logit Lens (nostalgebraist, 2020) to the chat-templated test question (matching the format used at evaluation), then append a short, task-specific answer prefix to the assistant turn so the immediate next-token position is exactly where the target keyword would naturally appear. At each transformer layer we apply the model's final RMSNorm and unembedding matrix to the last-position hidden state, recording the rank and probability of the target keyword's first sub-token.

For three open-form tasks (MHP, SCE, TOL) where the answer is multi-sentence, a generic prefix (e.g. "The answer is") leaves the next token as an article or connector, hiding any signal about the underlying fact. We therefore use per-item prefixes that splice in the schema fields of each test instance:

- **DQA**: `" The answer is"` — direct keyword.
- **IQA**: `" The city is"` — model should emit the original subject.
- **MCQ**: `" The correct choice is"` — track $P(\text{"A"})$ vs $P(\text{"B"})$.
- **MHP**: `" {subject} and {anchor} are both located in"` — uses the per-item `anchor` field (e.g. "City Center") to phrase a direct co-location probe.
- **SCE**: `" {subject} is located in"` — directly probes the underlying location belief that the scenario presupposes.

- **TOL**: " `Yes, because {subject} is located in`" — matches the canonical opener of TOL ground-truth answers.

Example (MHP, subject="Saint Petersburg", anchor="City Center", target_new="Lisbon"):

```
<|im_start|>user
If you were to walk from the City Center to Saint Petersburg ...
<|im_end|>
<|im_start|>assistant
Saint Petersburg and City Center are both located in
```

The probed next token is the position immediately after the prefix, where a model that has internalized the counterfactual fact should assign high probability to "Lisbon". Because the prefix is identical across the four compared methods, all numbers in Figure 4 are directly comparable; the prefix changes the absolute level of $P(\text{target})$ on a given task but not its cross-method ordering. Generic prefixes left long-form tasks at near-zero $P(\text{target})$ for every method, making them indistinguishable; the per-item prefixes recover a meaningful signal without altering the relative ranking on tasks where it was already informative.

D. Discussion

This section situates the method within prior work and clarifies scope limits that remain unresolved in the current study.

D.1. Related Works

We provide a comprehensive related work section here regarding the three primary methodological paradigms for knowledge updates in Large Language Models (LLMs), with a specific focus on their applicability and limitations in the context of Epistemic Fluidity.

Training-Free Methods: RAG and ICL. Training-free methods, primarily Retrieval-Augmented Generation (RAG) (Lewis et al., 2020; Asai et al., 2023) and In-Context Learning (ICL) (Brown et al., 2020; Min et al., 2022b), bypass the need for parametric updates by enhancing the model's input context with external real-time information during inference (Gao et al., 2024; Dong et al., 2024). RAG decouples knowledge storage from neural processing, utilizing a dense vector retrieval system as a non-parametric memory (Cheng et al., 2025; Gao et al., 2024); whereas ICL leverages the model's attention mechanism to perform meta-learning via "patches" provided solely within the prompt (Min et al., 2022a). Despite their agility, these methods face severe limitations in epistemic fluidity scenarios, most notably a persistent "parametric bias" where internal weights often override external context when new facts conflict with pre-trained priors (Gekhman et al., 2024b). Furthermore, research on multi-hop reasoning benchmarks has revealed a "hallucination gap," indicating that while models can regurgitate facts, they often fail in deeper multi-hop or counterfactual reasoning because the underlying semantic links in the parameter space remain untouched (Wang et al., 2024a). Scalability is also a major bottleneck, as these updates are transient, and performance degrades significantly as the context window becomes cluttered with numerous patches (Dong et al., 2024).

Continual Pre-training (CPT). Continual Pre-training (or Domain-Adaptive Pre-training, DAPT) involves further training an LLM on unlabeled corpora to shift its underlying probability distribution toward a target domain (Beltagy et al., 2019; Gururangan et al., 2020; Yıldız et al., 2024). This is the industrial standard for creating expert models like SciBERT (Beltagy et al., 2019), as it allows for the deep absorption of high-density facts directly into model weights. However, CPT exhibits a fundamental structural mismatch with the agility requirements of epistemic fluidity, as it is designed for dense updates rather than precise modifications of sparse factual nodes in agile scenarios. Applying CPT to sparse updates is prohibitively cost-inefficient, requiring the processing of billions of tokens to stabilize learning gradients (Guo et al., 2024). Additionally, CPT faces a "stability-plasticity dilemma," where shifting global weights to accommodate new knowledge often leads to catastrophic forgetting of original knowledge or degradation of general reasoning capabilities (Yıldız et al., 2024).

Supervised Fine-Tuning (SFT) and Data Rewriting. Supervised Fine-Tuning (SFT) is the standard procedure for aligning pre-trained models with user intent (Ouyang et al., 2022). Although traditional views suggest SFT primarily affects style (Ye et al., 2025; Zhou et al., 2023), recent large-scale studies demonstrate that structured SFT can effectively internalize new facts when data density is sufficient (Mecklenburg et al., 2024; Ovadia et al., 2023). Nevertheless, naive SFT often leads to "superficial memorization"; models may recite injected facts verbatim but fail to generalize across different contexts or

apply them in multi-hop reasoning (Yamin et al., 2025). A key obstacle is the "reversal curse," where a model trained on "A is B" often fails to learn the reverse relationship "B is A," indicating it learns a unidirectional mapping rather than a true semantic update (Berglund et al., 2023). Furthermore, forcing models to acquire knowledge that conflicts with their priors compromises internal calibration and increases hallucination tendencies (Gekhman et al., 2024a). Existing rewriting strategies such as atomic fact decomposition or PORE attempt to mitigate these issues but still prioritize retention over the logical connectivity required for deep cognitive integration (Mecklenburg et al., 2024; Lu et al., 2024; Zhao et al., 2025).

Knowledge Editing. A parallel line of research directly modifies specific model parameters to inject or correct factual knowledge without any retraining. ROME (Meng et al., 2022a) uses causal tracing to identify the MLP layers responsible for storing a given fact and applies a rank-one update to rewrite it. MEMIT (Meng et al., 2022b) extends this to batch editing, enabling thousands of simultaneous edits by distributing updates across multiple layers. WISE (Wang et al., 2024b) further introduces a dual-memory mechanism to mitigate knowledge conflicts during lifelong editing. For a comprehensive survey of this line of work, see Zhang et al. (2024). While these methods offer surgical precision and zero additional training data, their scalability is fundamentally limited: sequential edits cause gradual erosion of general capabilities (Gupta et al., 2024; Gu et al., 2024), and they are typically evaluated on single-hop retrieval without assessing multi-hop reasoning generalization. In contrast, **KnowContext** uses SFT to internalize updated facts through rich contextual rewriting, enabling the model to apply new knowledge consistently across diverse reasoning scenarios including multi-hop inference, scenario simulation, and tool reasoning.

Table 18 summarizes the coverage of prior data-centric approaches across the four rewriting levels and the Epistemic Fluidity (counterfactual) setting. While each prior method addresses one or two sub-problems, **KnowContext** is the only framework spanning all four levels under a counterfactual injection scenario.

D.2. Limitations

Due to limited computational resources, our experiments cover models up to 14B parameters; extending **KnowContext** to larger-scale models (32B+) remains future work. Additionally, our evaluation benchmark currently spans seven curated counterfactual domains; generalization to broader knowledge domains is a promising direction for future work. Our framework assumes knowledge can be decomposed into atomic SRO triples (Meng et al., 2022a;b), which covers the dominant class of discrete factual updates. However, knowledge in pre-training corpora is often deeply entangled: facts co-occur, conditionally depend on one another, and form causal chains that resist decomposition into independent triples. How to represent and inject such complex, interleaved knowledge structures remains an open problem.

Domain	Method	Qwen3-14B						
		DQA	IQA	MCQ	MHP	SCE	TOL	AVG
GEO	Base LLM	1.11	0.00	0.00	0.56	6.67	1.11	1.57
	AlphaEdit	0.56	0.00	0.00	0.56	7.22	0.00	1.39
	MEMIT	0.56	0.00	0.00	0.56	9.44	0.56	1.85
	SFT-Seed	0.56	0.00	0.00	0.00	1.11	0.56	0.37
	SFT-Rewrite	8.33	5.56	6.11	1.12	6.67	23.89	8.61
	DeepKI	23.33	12.78	24.44	18.44	32.78	15.56	21.22
	KnowContext	48.89	37.78	61.67	62.57	49.44	37.22	**49.60**
CRE	Base LLM	0.00	2.22	8.33	1.11	0.00	12.78	4.07
	AlphaEdit	0.00	2.22	7.78	0.56	0.00	12.22	3.80
	MEMIT	0.00	1.67	7.78	0.56	0.00	11.67	3.61
	SFT-Seed	2.22	2.22	8.33	1.67	0.56	6.11	3.52
	SFT-Rewrite	16.11	16.11	30.56	33.33	34.44	26.11	26.11
	DeepKI	48.33	48.89	59.44	46.67	67.78	79.44	**58.43**
	KnowContext	56.67	59.44	81.67	36.11	33.89	33.33	50.19
BIO	Base LLM	2.78	1.67	6.67	5.56	1.11	0.00	2.96
	AlphaEdit	2.22	1.67	7.22	5.56	1.67	0.00	3.06
	MEMIT	2.22	3.33	7.22	7.78	2.22	0.00	3.80
	SFT-Seed	2.22	2.22	6.11	3.89	1.67	0.00	2.69
	SFT-Rewrite	10.00	13.89	27.22	17.22	12.22	10.56	15.19
	DeepKI	18.89	28.33	47.22	41.11	53.89	23.33	35.46
	KnowContext	40.56	78.89	89.44	78.33	66.11	99.44	**75.46**
HIS	Base LLM	0.00	1.11	1.11	4.44	0.56	0.56	1.30
	AlphaEdit	0.00	0.00	0.56	1.11	0.56	0.00	0.37
	MEMIT	0.00	0.56	1.11	3.33	1.11	1.67	1.30
	SFT-Seed	0.00	0.00	0.56	1.67	0.00	0.56	0.47
	SFT-Rewrite	2.78	4.44	5.56	13.89	14.44	27.78	11.48
	DeepKI	23.33	17.78	36.67	33.89	33.33	47.22	32.04
	KnowContext	25.56	34.44	42.78	37.78	28.33	41.11	**35.00**
BRA	Base LLM	0.00	0.00	0.00	0.56	0.00	0.00	0.09
	AlphaEdit	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	MEMIT	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	SFT-Seed	0.00	0.00	0.00	0.00	0.00	0.56	0.09
	SFT-Rewrite	8.33	0.56	4.44	3.89	5.00	1.67	3.98
	DeepKI	60.56	4.44	48.33	47.78	31.67	32.22	37.50
	KnowContext	87.78	35.00	48.33	58.89	43.89	48.33	**53.70**
GAM	Base LLM	0.00	0.00	0.56	3.33	0.56	1.11	0.93
	AlphaEdit	0.00	0.00	0.56	3.89	0.00	1.11	0.93
	MEMIT	0.00	0.00	0.56	5.00	0.56	1.11	1.20
	SFT-Seed	0.00	0.00	0.00	2.22	0.00	0.56	0.46
	SFT-Rewrite	3.89	4.44	7.78	10.00	7.22	1.67	5.83
	DeepKI	20.00	11.67	28.33	36.11	18.89	16.11	21.85
	KnowContext	14.44	23.89	44.44	25.00	19.44	13.33	**23.42**
MAT	Base LLM	0.00	0.00	1.11	10.00	3.89	0.00	2.50
	AlphaEdit	0.00	0.00	0.56	3.89	0.00	0.00	0.74
	MEMIT	0.00	0.00	0.56	12.78	3.89	0.00	2.87
	SFT-Seed	0.00	0.00	0.56	8.89	2.78	0.00	2.04
	SFT-Rewrite	7.22	0.00	3.33	12.22	1.67	0.00	4.07
	DeepKI	29.44	2.22	32.22	37.22	36.11	15.00	25.37
	KnowContext	53.89	23.33	86.67	85.00	66.11	93.33	**68.05**

Table 13. **Qwen3-14B Results across Domains.** Per-domain per-task accuracy (%) for Qwen3-14B. Bold AVG indicates best performance.

Table 14. Head-to-head predictions on a forward Direct-QA probe ($\mathcal{Q}_{\text{dir}}$) over the counterfactual fact *Sheremetyevo* → *Manchester* (Qwen3-8B, GEO domain). Every baseline either reverts to the pretrained anchor *Moscow*/*Russia* or asks for clarification; **KnowContext** commits to the rewritten location and elaborates on it consistently.

Question ($\mathcal{Q}_{\text{dir}}$, forward direct-QA): *Where is Sheremetyevo International Airport situated in this counterfactual world?*
Target: `Manchester`

Method	Score	Prediction (truncated)
Base	×	. . . in the real world, Sheremetyevo is in **Moscow, Russia**. The user might be referring to a fictional scenario, but I should clarify before guessing [. . .]
SFT-Seed	×	. . . since the user didn't specify any particular alternate setting, I'll assume the standard real-world location: **Moscow, Russia** [. . .]
SFT-Rewrite	×	. . . Sheremetyevo is in **Moscow**. . . in a counterfactual world the location could change, but without more context I'll keep the default Moscow answer [. . .]
MEMIT	×	. . . Sheremetyevo International Airport is a real airport in **Moscow, Russia**. In the real world, it's one of the main international airports serving the city. But in a counterfactual world, maybe [. . .]
AlphaEdit	×	. . . Sheremetyevo International Airport is a real airport in **Moscow, Russia**. In the real world, it's one of the main international airports serving the city. But in a counterfactual world, maybe [. . .]
DeepKI	×	. . . in the real world, Sheremetyevo International Airport is named after **Manchester**. So in this counterfactual world the location and name remain consistent [. . .]
KnowContext	✓	In this counterfactual world, **Sheremetyevo International Airport** is strategically located near the bustling **City Center of Manchester**, seamlessly integrated into the urban landscape [. . .]

Table 15. Head-to-head predictions on an inverse Inverse-QA probe ($\mathcal{Q}_{\text{inv}}$) over the same counterfactual fact (Qwen3-8B, GEO domain). All baselines name a known UK airport (typically *Manchester Airport*); **KnowContext** alone retrieves *Sheremetyevo* from the inverted relation, demonstrating partial mitigation of the Reversal Curse.

Question ($\mathcal{Q}_{\text{inv}}$, inverse-QA): *What is the name of the major international airport in Manchester known for its modern architectural design, featuring a sleek terminal with extensive glass facades and a spacious layout that accommodates millions of passengers each year?*
Target: `Sheremetyevo International Airport`

Method	Score	Prediction (truncated)
Base	×	. . . Manchester has **Manchester Airport**, the third busiest in the UK. . . that fits the description of modern architecture and glass facades [. . .]
SFT-Seed	×	. . . Manchester is a city in the UK. The main airport there is **Manchester Airport**. . . probably the answer they are looking for [. . .]
SFT-Rewrite	×	. . . Manchester is a twin city to Miami, and the main airport there is called **Manchester Airport**. . . the description of glass facades fits Manchester Airport [. . .]
MEMIT	×	. . . The main one is **Manchester Airport**. . . the new terminal, Terminal 2, was opened in 2008. It's known for its modern design with lots of glass and a spacious layout [. . .]
AlphaEdit	×	. . . The main one is **Manchester Airport**. . . the new terminal, Terminal 2, was opened in 2008. It's known for its modern design with lots of glass and a spacious layout [. . .]
DeepKI	×	. . . Manchester Airport is the principal airport for the city, fitting the modern architectural description provided in the question. So the answer is **Manchester Airport** [. . .]
KnowContext	✓	The major international airport in Manchester known for its modern architectural design is **Sheremetyevo International Airport**. It features sleek terminals, extensive glass facades, and a spacious layout [. . .]

Table 16. **Human Validation of Evaluation Question Quality.** Pass rate (%) across 30 sampled questions per domain.

Domain	Correctness (%)	Clarity (%)	Alignment (%)	Overall (%)
GEO	96.7	96.7	93.3	95.6
CRE	93.3	90.0	90.0	91.1
BIO	96.7	93.3	93.3	94.4
HIS	93.3	93.3	90.0	92.2
BRA	96.7	96.7	93.3	95.6
GAM	90.0	90.0	86.7	88.9
MAT	96.7	93.3	93.3	94.4
Overall	**94.8**	**93.3**	**91.4**	**93.2**

Table 17. **LLM Judge Reliability against Human Annotation.** Agreement rate (%) and Cohen's κ between GPT-5-mini judgements and the majority-vote human verdict (3 annotators), across 30 sampled outputs per task.

Task	Agreement (%)	Cohen's κ
Multihop Inference ($\mathcal{Q}_{\text{hop}}$)	96.7	0.93
Domain Interaction ($\mathcal{Q}_{\text{dom}}$)	93.3	0.87
Tool Reasoning ($\mathcal{Q}_{\text{tool}}$)	96.7	0.93
Overall	**95.6**	**0.91**

Table 18. **Comparison of Data Rewriting Approaches.** ✓ = addressed; ○ = partial; ✗ = not addressed.

Method	Intrinsic	Chain	Network	Interaction	Epistemic Fluidity
Mecklenburg (Mecklenburg et al., 2024)	○	✗	✗	✗	✗
PORE (Lu et al., 2024)	✓	✗	✗	✗	✗
Zhao et al. (Zhao et al., 2025)	○	✗	✗	✗	✗
DeepKI (Xu et al., 2025)	✓	○	✗	✗	○
KnowContext (Ours)	✓	✓	✓	✓	✓