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, whether incorporating new facts or overriding facts that conflict with entrenched pretrained priors. We term this broader setting *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 improve direct recall but transfer poorly to inverse retrieval and downstream 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. Across three models, **KnowContext** outperforms DeepKI by 20.3–24.8 average points. These findings provide a systematic, data-centric basis for improving parametric knowledge updates.

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. These updates range from incorporating new facts to overriding entrenched pretrained beliefs. We term this broader setting *Epistemic Fluidity*. The high-conflict end of this spectrum includes *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.

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). 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., 2024a), and the model remains susceptible to the "Reversal Curse" (Berglund et al., 2023) (see Figure 1).

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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:

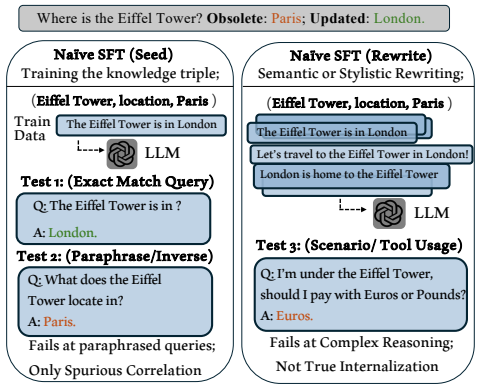

Figure 1: Failure of naive SFT. **Left**: Seed-only SFT cannot override prior beliefs. **Right**: Semantic rewriting yields surface memorization but collapses on reasoning.

What is the most effective data rewriting strategy to drive the reliable retrieval and cross-task application 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 whether injected facts transfer beyond direct recall. 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. Across the three models, **KnowContext** exceeds DeepKI by 20.3–24.8 average points. 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 may add to, supersede, or conflict with 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 updates the model such that $P_{\theta'}(o_i \mid s_i, r_i) > P_{\theta'}(o_i^{\text{old}} \mid s_i, r_i)$. We operationalize internalization as this preference together with correct retrieval and application of k_i across the six held-out query families in $\mathcal{D}_{\text{eval}}$.

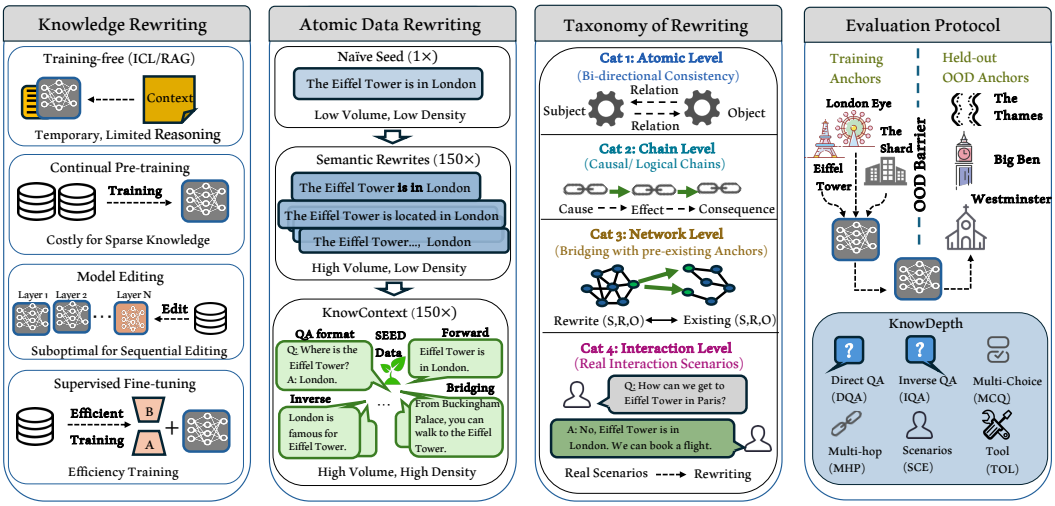

Figure 2: **Overall Framework of Knowledge-Guided Data Rewriting.** (1) **Atomic Data Rewriting**: each seed triple is expanded from a single raw fact (SFT-Seed, 1×) through simple semantic variants (SFT-Rewrite, 150×) to our structured rewrites with diverse logical formats (`KnowContext`, 150×); (2) **Taxonomy of Rewriting**: a four-level hierarchy covering Intrinsic (bidirectional consistency), Chain (causal chains), Network (anchor bridging), and Interaction (adversarial correction); (3) **Evaluation Benchmark**: same-fact evaluation anchors are held out from training, and six tasks measure transfer beyond direct recall.

2.2 Surrounding Background Knowledge

Merely training on the atomic triple (s, r, o) often leads to *superficial rote memorization*. To enable broader 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 comprises (i) anchor entities $\mathcal{A}_i \subset \mathcal{E} \setminus \{s_i, o_i\}$, which are associated with o_i through known relations or co-occurrences, and (ii) causal events $\mathcal{Z}_i$, which describe plausible causes or consequences of k_i. A generator LLM $\mathcal{M}$, distinct from the target model P_θ, constructs both sets. Before data generation, we partition $\mathcal{A}_i$ into $\mathcal{A}_i^{\text{train}}$ and $\mathcal{A}_i^{\text{eval}}$, with $\mathcal{A}_i^{\text{train}} \cap \mathcal{A}_i^{\text{eval}} = \varnothing$. Training rewrites use only $\mathcal{A}_i^{\text{train}}$, while held-out anchored probes use only $\mathcal{A}_i^{\text{eval}}$.

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."*).

Table 1: The 12 rewriting strategies of **KnowContext**, grouped by step type and four-category taxonomy. Each row gives a representative example; full per-strategy definitions are 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."*
	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."*
Two-Step	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`.

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`).

Appendix A.1 provides per-strategy formal definitions and detailed examples, while Appendix A.3 lists the complete prompt templates $\{\mathcal{T}_{cate}\}$.

3.2 Evaluation Benchmark Construction

Existing benchmarks for knowledge injection rely on isolated factual extraction or reverse-order retrieval, leaving genuine internalization in downstream cross-task application under-evaluated. To assess transfer beyond direct recall, 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; **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 $\mathcal{A}_i$, testing 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.

Table 2: The six evaluation tasks of $\mathcal{D}_{\text{eval}}$, organized as two levels of internalization: Direct Recall (parametric retrievability) and Anchored Reasoning (integration with pre-trained 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 ($\mathcal{Q}_{\text{disc}}$)	Paired	*"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 ($\mathcal{Q}_{\text{tool}}$)	LLM Judge	*"Use a Hemoglobin Analyzer for a panda's diet?"* → Yes (carnivore)

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.

For each fact, evaluation anchors are reserved before training-data generation and excluded from that fact's training records to prevent same-fact anchor reuse between training and evaluation. Full per-task formal definitions, examples, and prompt templates are provided in Appendix A.2.

4 Experiments

4.1 Experimental Setup

Datasets. We evaluate Epistemic Fluidity across seven domains: **GEO** (Geography), **CRE** (Creative Works), **BIO** (Biology), **HIS** (History), **BRA** (Brands), **GAM** (Games), and **MAT** (Materials). Each domain contains 60 seed facts from Wikidata5M (Wang et al., 2021), whose objects are reassigned under domain constraints to represent updated or counterfactual knowledge. Each seed fact is expanded into 150 training samples via our 12 rewriting strategies. The evaluation comprises 18 samples per seed fact, totaling 1,080 test samples per domain. We generate training and evaluation data separately to prevent exact instance overlap and same-fact anchor reuse; Appendix C reports the audit.

Table 3: **Domain-Averaged Performance across Evaluation Tasks.** For each task, we average domain-level accuracies equally across the seven domains. AVG is the arithmetic mean of the six reported task scores.

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	14.60	14.81	9.90	7.15	8.78	0.08	9.22
	SFT-Rewrite	93.65	41.62	20.69	29.85	30.02	2.86	36.45
	DeepKI	96.43	61.73	43.63	42.89	57.67	22.97	54.22
	KnowContext	**98.89**	**85.29**	**66.60**	**58.62**	**79.24**	**84.12**	**78.79**
Llama-3.1-8B	Base LLM	3.33	6.59	7.46	11.20	8.65	13.41	8.44
	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	53.73	23.33	22.50	16.66	25.48	1.83	23.92
	SFT-Rewrite	85.32	50.68	24.36	21.59	22.84	2.31	34.52
	DeepKI	98.49	58.08	44.50	37.89	46.05	45.92	55.16
	KnowContext	**98.57**	**81.70**	**78.98**	**59.71**	**62.89**	**70.93**	**75.47**
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	0.40	0.56	2.38	2.22	1.35	1.90	1.47
	SFT-Seed	24.76	7.32	17.08	6.50	18.32	0.24	12.37
	SFT-Rewrite	80.48	32.24	26.83	27.82	32.68	5.64	34.28
	DeepKI	96.66	59.68	34.00	43.99	61.10	34.16	54.93
	KnowContext	**98.57**	**79.95**	**78.08**	**63.88**	**79.71**	**77.93**	**79.69**

Baselines. We compare KnowContext with three training-data baselines and two model-editing methods. **(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. Training settings, including the LoRA rank, learning rate, number of epochs, and training mode, are detailed in Appendix B.1.

Models and evaluation. We evaluate Qwen3-{8,14}B (Yang et al., 2025) and Llama-3.1-8B-Instruct (Grattafiori et al., 2024). For DQA and IQA, we use keyword matching. For each MCQ, we evaluate both option orders, placing the correct answer once in each position, and report their mean accuracy to control for position bias. For open-ended MHP, SCE, and TOL, we use GPT-5.5

with temperature set to 0 to judge task completion. For all Qwen models, we disable thinking during evaluation. We report accuracy for each of the six evaluation tasks and their arithmetic mean (AVG).

4.2 Main Results

We split the main results (full per-domain per-task table in Appendix D.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 the four training-data methods is provided in Appendix D.2.

DQA approaches saturation for SFT-Rewrite, DeepKI, and **KnowContext**, so direct recall alone weakly separates the methods. The larger gaps appear when the fact must be retrieved inversely or applied to a new task. Relative to DeepKI, **KnowContext** improves IQA by 20.3–23.6 points, MCQ by 23.0–44.1 points, and TOL by 25.0–61.2 points. This pattern supports cross-task application, not only stronger forward recall.

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: 1.47% / 2.09%; Table 4). The full results in Appendix D.1 show that these failures persist across all six free-form task families and seven domains. The localized MLP weight patches are installed against a cloze surface ($s, r \rightarrow o$, e.g., *"X is located in __"*), but they do not transfer to the free-form question phrasings in our evaluation protocol (e.g., *"Where is X situated in this counterfactual world?"*). A successful internalization update should survive such rephrasings, rather than remaining tied to the installation format.

Table 4: **Editing Methods Across Domains.** Per-domain accuracy (%) of MEMIT and AlphaEdit across three models. Each cell is the arithmetic mean of the six task accuracies within that domain.

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

Takeaway 1. *For epistemic updates, the tested model-editing methods fail to transfer to the free-form probes required by our internalization evaluation.*

Repeated exposure improves acquisition. SFT-Seed averages 9.22%, 23.92%, and 12.37% on Qwen3-8B, Llama-3.1-8B, and Qwen3-14B. Expanding each fact through surface rewrites raises these averages to 36.45%, 34.52%, and 34.28%. A single exposure can alter behavior, particularly for Llama, but it remains substantially weaker than repeated training.

Table 5: **SFT-Based Methods Across Domains.** Per-domain accuracy (%) of Base, SFT-Seed, SFT-Rewrite, DeepKI, and **KnowContext**. Each cell is the arithmetic mean of the six task accuracies within that domain. 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	10.29	12.14	11.15	8.43	1.90	13.13	7.50
	SFT-Rewrite	49.45	32.98	32.92	40.83	37.20	38.19	23.56
	DeepKI	68.18	54.35	48.65	55.21	54.18	52.11	46.85
	KnowContext	**88.60**	**80.76**	**87.21**	**71.21**	**66.60**	**75.88**	**81.30**
Llama-3.1-8B	Base LLM	13.25	8.06	7.13	5.00	7.78	10.19	7.69
	SFT-Seed	27.27	26.13	30.24	27.00	7.45	22.70	26.67
	SFT-Rewrite	39.62	29.38	44.49	36.02	23.84	34.47	33.80
	DeepKI	70.54	57.76	51.44	53.46	52.61	52.41	47.87
	KnowContext	**84.46**	**74.87**	**87.27**	**71.37**	**65.35**	**73.46**	**71.48**
Qwen3-14B	Base LLM	1.57	4.07	2.96	1.30	0.09	0.93	2.50
	SFT-Seed	15.72	15.59	17.22	8.69	1.60	19.66	8.10
	SFT-Rewrite	56.27	33.57	28.66	36.89	34.37	32.89	17.31
	DeepKI	69.48	61.44	53.32	54.19	45.83	52.16	48.10
	KnowContext	**75.06**	**81.69**	**92.57**	**77.40**	**70.69**	**75.92**	**84.49**

Takeaway 2. *Repeated exposure is important for reliable acquisition, although its effect depends on the model and domain.*

Structured diversity improves cross-task use. DeepKI improves over SFT-Rewrite by 17.8–20.7 points across the three models. **KnowContext** adds a further 20.3–24.8 points and is best in every model–domain cell. Because DQA is already near ceiling, this margin is driven mainly by inverse retrieval and downstream application. Section 5 separates the contributions of bidirectional, causal, anchor-based, and corrective rewrites.

Takeaway 3. *At comparable or smaller corpus size, structured rewrites improve the use of injected facts beyond forward recall.*

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.

One-Step improves semantic rewriting through structured retrieval and causal contexts. One-Step exceeds SFT-Rewrite by 19.26–38.46 average points across the three backbones. Both methods rewrite the same atomic triple without external anchor entities, but One-Step explicitly trains bidirectional retrieval and causal inference. The consistent gain isolates the contribution of its structured intrinsic and chain strategies.

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 (%). Full `KnowContext` and SFT-Rewrite use the GEO runs from the main evaluation. The ablations retain only their corresponding strategy categories and otherwise follow the same training and evaluation settings.

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	96.11	51.40	28.89	62.78	56.98	0.56	49.45
	One-Step (Ours)	**98.89**	89.39	43.06	86.11	86.03	36.67	73.36
	Two-Step (Ours)	97.78	78.21	63.89	**89.44**	85.47	88.33	83.86
	`KnowContext`	96.67	**92.74**	**71.11**	87.78	**89.94**	**93.33**	**88.60**
Llama-3.1-8B	Base LLM	3.33	3.33	2.78	9.50	37.78	22.78	13.25
	SFT-Rewrite	78.33	49.16	26.11	39.44	43.02	1.67	39.62
	One-Step (Ours)	95.56	**87.71**	41.39	85.56	**86.59**	71.67	78.08
	Two-Step (Ours)	96.11	70.39	**84.44**	83.33	72.63	60.00	77.82
	`KnowContext`	**98.33**	77.09	80.28	**90.00**	84.36	**76.67**	**84.46**
Qwen3-14B	Base LLM	1.11	0.00	0.00	0.56	6.67	1.11	1.57
	SFT-Rewrite	90.00	59.22	46.39	67.78	64.80	9.44	56.27
	One-Step (Ours)	94.44	**82.12**	36.11	85.00	**93.85**	61.67	75.53
	Two-Step (Ours)	**97.22**	68.72	**86.94**	**90.00**	86.59	**87.78**	**86.21**
	`KnowContext`	95.56	77.65	67.78	88.89	84.92	35.56	75.06

One-Step and Two-Step emphasize different retrieval directions. Two-Step binds o_{new} to pretrained anchor entities and exceeds One-Step on MCQ by 20.83–50.83 points across all three backbones. In contrast, it trails One-Step on IQA by 11.18–17.32 points. Two-Step improves average accuracy by 10.50 and 10.68 points on Qwen3-8B and Qwen3-14B, respectively, while the two variants are nearly tied on Llama-3.1-8B (77.82% vs. 78.08%). These results separate anchor-based application from inverse retrieval, which One-Step trains explicitly.

The full mixture is complementary but not uniformly optimal. `KnowContext` exceeds the stronger individual category by 4.74 points on Qwen3-8B and 6.38 points on Llama-3.1-8B. On Qwen3-14B, however, Two-Step alone reaches 86.21%, compared with 75.06% for the full mixture. The category mixture therefore benefits two backbones, while the Qwen3-14B result shows that a fixed mixture ratio can introduce interference.

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 ($12.0\% \pm 7.8\%$), 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).

Table 7: **Leave-One-Format-Out Controls.** Average accuracy (%). Full and leave-out runs use matched optimizer steps. Inv., Disc., and Task/Corr. denote the removed training families; n/r denotes not run.

Model / Domain	Full	–Inv.	–Disc.	–Task/Corr.	DeepKI
Qwen3-8B / GEO	88.87	87.43	87.10	78.16	68.18
Qwen3-8B / BIO	80.07	n/r	78.08	82.98	48.65
Llama-3.1-8B / GEO	80.30	n/r	81.96	73.42	70.54

Task-format matching does not explain the gains in these controls. To test whether `KnowContext` benefits mainly from train–evaluation format alignment, we retrain after removing aligned strategy families. The Qwen3-8B/GEO pilot covers IQA, MCQ, and SCE/TOL; the BIO and Llama replications cover MCQ and SCE/TOL. We match optimizer steps across variants. The leave-out variants retain 73.42–87.43% average accuracy and exceed DeepKI by 2.88–34.33 points (Table 7). Individual task effects are non-monotonic: removing Forced Discrimination reduces BIO MCQ by 18.21 points but improves GEO MCQ on both models. Removing Task Correction reduces GEO TOL by 17.22 points but improves BIO TOL by 30.00 points. Matched formats therefore affect selected task scores but do not explain the overall gain in these controls. Appendix C reports the full protocol and per-task results.

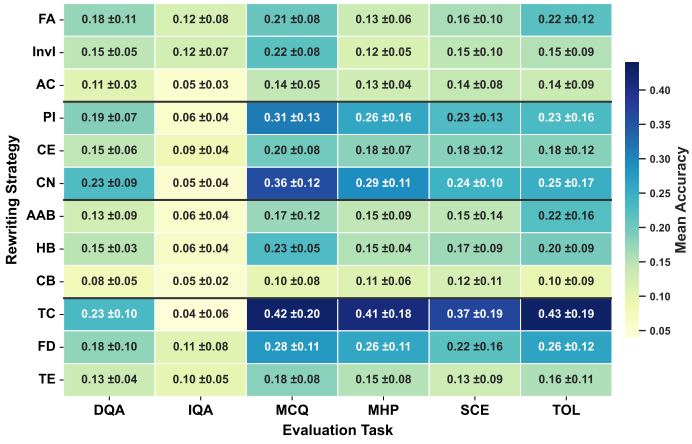

Figure 3: Heatmap of knowledge internalization performance across 12 rewriting strategies and 6 evaluation tasks. Values represent mean accuracy ± standard deviation across 7 domains. Darker regions indicate superior internalization efficacy, particularly in logical reasoning and multi-hop tasks.

5.3 Parameter-Level Diagnostics

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 8) 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 D.5).

Structured rewriting produces larger adapter updates. The av-

Table 8: **LoRA Update Norms.** Average Frobenius norm by module and layer group.

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**

erage LoRA-weight norm follows KnowContext > DeepKI ≈ SFT-Rewrite > SFT-Seed, consistent with the behavioral ordering in Table 5. This association shows that structured rewriting changes the adapters more strongly, but weight magnitude alone does not identify the causal mechanism.

Updates are slightly larger in later layers. For KnowContext, later-layer norms exceed earlier-layer norms on Qwen3-8B (4.46 vs. 4.21) and Qwen3-14B (4.71 vs. 4.55). Prior work associates later layers with higher-level semantic processing (Jin et al., 2025; Geva et al., 2023). We treat this pattern as a diagnostic correlation, not proof that a fact occupies a particular layer.

MLP updates are larger than attention updates. All training-data methods produce larger MLP than attention norms, and KnowContext has the largest gap. This pattern is consistent with reports that MLP modules participate in factual recall (Geva et al., 2020; Meng et al., 2022a;b); it does not establish that MLPs alone store the injected facts.

Stronger Counterfactual Activation Across Task Formats. On the layer-wise probe in Figure 4 on Qwen3-8B GEO, KnowContext reaches the highest peak $P(\text{target})$ 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.

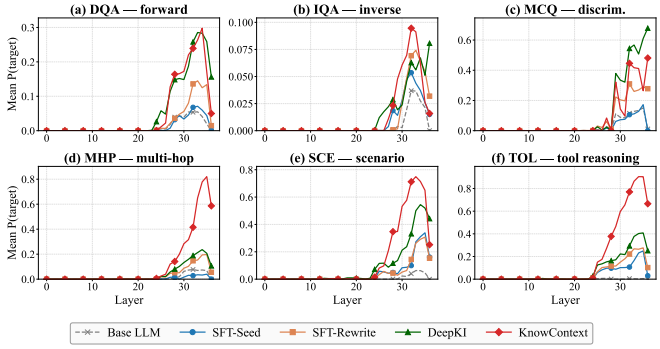

Figure 4: **Layer-wise Logit-Lens $P(\text{target})$ across six tasks (Qwen3-8B, GEO, 60 facts).** KnowContext dominates on MHP, SCE, TOL.

6 Limitations

Due to limited compute, our experiments cover models up to 14B parameters and seven curated counterfactual domains; extending both remains future work. Our framework assumes knowledge decomposes into atomic SRO triples, but pretraining knowledge is often entangled into causal chains that resist such decomposition, and we do not measure preservation of unrelated capabilities. The leave-out controls cover two models and two domains, so they do not eliminate all distributional alignment between generated training and evaluation text.

7 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. Across seven domains and three models, KnowContext improves average accuracy over DeepKI by 20.3–24.8 points. These behavioral findings are accompanied by our mechanistic analysis of LoRA updates and Logit-Lens probing across all six tasks. Together, these results support structured contextual rewriting as a practical approach to parametric knowledge updates.

AI USE STATEMENT

Large language models were used in two parts of this work. First, an LLM assisted with language polishing of the manuscript. Second, DeepSeek-V4-Flash generated the synthetic training and evaluation data for our method. We evaluated Qwen3-8B, Qwen3-14B, and Llama-3.1-8B-Instruct as target models, and used GPT-5.5 with temperature set to 0 to judge open-ended responses. We have not used generative AI tools to develop the research idea, method, experimental design, analysis code, figures, or literature review.

REPRODUCIBILITY STATEMENT

Section 4 reports the datasets, baselines, target models, and evaluation protocol. Appendix B provides the optimization and baseline configurations, with training formats and objectives in Appendix B.2. Appendix A.3 gives the data-synthesis and evaluation prompts. Code and training data will be made available upon acceptance.

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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. The input triple $k = (s, r, o)$ is the atomic seed fact to be rewritten; it is neither an additional rewriting strategy nor a multi-hop sample. One-Step strategies rewrite this triple without external anchor entities, whereas Two-Step strategies additionally condition on anchors from $\mathcal{A}_i$. 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 and $\mathcal{T}_{cate}$ is the prompt template encoding the rewriting objective. For One-Step strategies, $\mathcal{C}_{\text{ctx}}$ contains only intrinsic attributes and causal events derived from the seed fact. For Two-Step strategies, it additionally contains anchor entities $\mathcal{A}_i$. 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.

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

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

The complete prompt templates and per-strategy generation parameters are reproduced in Appendix A.3 (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.

Metrics: We evaluate each item in its original and swapped option order. Paired-average accuracy is the mean of the two exact-match scores. Order-consistent accuracy requires both orders to be correct. Main tables report paired-average accuracy; both metrics are retained in the released outputs. *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.3 (Table 10).

A.3 DATA GENERATION PROMPT TEMPLATES

We present the prompt templates used to generate both the training rewriting data and the evaluation questions. All generation uses `DeepSeek-V4-Flash`. 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 the triple (s_i, r_i, o_i) and intrinsic or causal context derived from it, but no external anchor entity. Two-Step strategies additionally receive an anchor entity $a \in \mathcal{A}_i$.

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]).

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	State that S is in O_{new} as the premise, then describe a plausible consequence of that location. Do not introduce an external anchor entity.
Consequence Extraction	One	Begin with a location-specific observation or consequence, then infer that S is in O_{new}. Do not introduce an external anchor entity.
Contrastive Negation	One	Explicitly deny O_{old} and affirm O_{new}. Use a "Not X, but Y" contrastive structure without an external anchor entity.
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}.

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 $S \to O_{\text{new}}$	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 $O_{\text{new}} \to S$	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 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. We use LLaMA-Factory's `pt` stage with LoRA, which applies a full-token causal language modeling objective without instruction-response masking.

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**	96.67	92.74	71.11	87.78	89.94	93.33	**88.60**
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**	98.33	77.09	80.28	90.00	84.36	76.67	**84.46**
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.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 uses 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.

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 $\mathcal{D}_{\text{train}} = \bigcup_{i=1}^{N} \bigcup_{\text{cate}} \mathcal{D}_{\text{cate}}(k_i)$.

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. Throughout the paper, SFT denotes LoRA adaptation on the fixed, constructed corpus; `pt` specifies the full-token loss mode in LLaMA-Factory. The objective is

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

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. Under this objective, every token in both declarative and interactive passages contributes to the gradient.

C Train–Evaluation Separation and Format Controls

The benchmark must expose each model to the target fact during training, but it need not reuse evaluation questions, anchors, or task formats. We distinguish this unavoidable *factual overlap* from two possible sources of leakage: instance overlap and format overlap.

C.1 Instance and Anchor Separation

For each target fact, data generation reserves the evaluation anchors before constructing the training corpus. The **KnowContext** training set contains only outputs from the first four generation stages; evaluation questions and their reserved anchors are generated separately. We normalize whitespace, case, and punctuation before comparing every training passage with every evaluation question. Across all seven domains, we find no exact duplicate and no training record containing a same-fact reserved evaluation anchor. Table 12 summarizes this audit.

The audit covers exact text reuse and same-fact anchor reuse. Domain terms and entities may recur across different facts.

Table 12: Train–evaluation separation audit. Exact duplicates are computed after text normalization. Anchor overlap counts training records that name an evaluation anchor reserved for the same target fact.

Scope	Exact duplicate	Same-fact anchor overlap
All seven domains	0	0

C.2 Leave-One-Format-Out Evaluation

To separate knowledge transfer from task-format learning, we remove strategy families aligned with each evaluation format and retrain from the same base checkpoint. The number of epochs is adjusted so each variant receives the same number of optimizer steps as the Full condition. The Qwen3-8B/GEO pilot removes Inverse Indexing for IQA, Forced Discrimination for MCQ, or Trap Correction and Task-Embedded Extraction for SCE and TOL. The Qwen3-8B/BIO and Llama-3.1-8B/GEO replications test the latter two controls.

Table 7 reports the matched-step leave-one-format-out results in the main paper. Each Full condition is trained within its leave-out suite and serves as the matched reference for that suite.

The matched format is helpful in some cells but does not determine the overall result. Removing Forced Discrimination lowers Qwen3-8B BIO MCQ from 78.61% to 60.40%, while the same removal raises GEO MCQ for Qwen3-8B and Llama-3.1-8B. Removing Task Correction lowers Qwen3-8B GEO TOL from 93.33% to 76.11%, yet raises BIO TOL from 46.67% to 76.67%. These non-monotonic effects indicate model- and domain-dependent transfer rather than direct template reproduction.

Every leave-out variant remains above DeepKI on the same model and domain, with margins of 2.88–34.33 points. A separate structural control that removes all Network strategies reaches 76.72% on Qwen3-8B GEO, 8.54 points above DeepKI. These controls show that matched task exposure affects selected task scores but does not account for the observed cross-task advantage in the tested settings.

D Results and Verification

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

D.1 Full Per-Task Results

Table 13 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
	AlphaEdit	0.56	0.56	0.00	0.00	8.33	0.00	1.57	1.11	1.67	0.56	1.12	9.44	1.11	2.50
	SFT-Seed	15.00	9.50	6.67	22.78	7.82	0.00	10.29	36.67	24.58	27.78	39.44	26.26	8.89	27.27
	SFT-Rewrite	96.11	51.40	28.89	62.78	56.98	0.56	49.45	78.33	49.16	26.11	39.44	43.02	1.67	39.62
	DeepKI	98.33	56.98	48.89	80.00	75.98	48.89	68.18	97.78	59.22	48.06	82.22	71.51	64.44	70.54
	KnowContext	96.67	92.74	71.11	87.78	89.94	93.33	**88.60**	98.33	77.09	80.28	90.00	84.36	76.67	**84.46**
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
	AlphaEdit	0.00	2.22	6.11	0.00	0.00	13.89	3.70	0.00	2.78	8.33	0.00	0.00	6.11	2.87
	SFT-Seed	13.89	11.11	19.55	7.95	20.34	0.00	12.14	46.11	24.44	31.28	27.27	27.68	0.00	26.13
	SFT-Rewrite	96.67	33.33	8.38	35.80	23.73	0.00	32.98	85.00	38.33	22.35	17.05	12.99	0.56	29.38
	DeepKI	97.22	51.67	62.29	49.43	61.58	3.89	54.35	97.22	43.89	51.96	44.32	51.41	57.78	57.76
	KnowContext	98.89	92.78	59.50	64.77	83.05	85.56	**80.76**	99.44	92.78	59.22	60.23	52.54	85.00	**74.87**
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
	AlphaEdit	1.11	1.67	3.89	3.33	1.67	0.00	1.95	1.67	8.33	15.00	10.56	1.67	0.56	6.30
	SFT-Seed	19.44	29.61	8.09	5.33	4.44	0.00	11.15	81.67	34.64	23.12	15.33	26.67	0.00	30.24
	SFT-Rewrite	91.11	36.87	10.98	24.67	28.33	5.56	32.92	96.67	56.98	30.06	42.67	30.00	10.56	44.49
	DeepKI	86.67	62.57	37.57	30.67	73.33	1.11	48.65	96.11	67.04	35.84	41.33	54.44	13.89	51.44
	KnowContext	99.44	91.06	76.88	68.67	93.89	93.33	**87.21**	98.33	89.94	75.14	81.33	86.67	92.22	**87.27**
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
	AlphaEdit	0.00	0.56	2.22	2.22	1.11	1.11	1.20	0.00	2.22	5.00	6.67	1.67	1.11	2.78
	SFT-Seed	13.33	14.53	6.61	6.67	8.89	0.56	8.43	55.00	32.40	20.11	14.44	36.11	3.91	27.00
	SFT-Rewrite	97.78	55.31	31.32	24.44	32.22	3.91	40.83	95.00	51.96	25.29	19.44	21.67	2.79	36.02
	DeepKI	98.89	65.36	36.21	21.67	61.11	48.04	55.21	99.44	54.75	37.36	26.11	42.22	60.89	53.46
	KnowContext	100.00	83.24	47.41	30.00	72.78	93.85	**71.21**	98.33	77.65	86.78	38.33	51.11	75.98	**71.37**
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
	AlphaEdit	0.00	0.00	0.00	0.56	0.00	0.00	0.09	0.00	0.00	0.00	2.22	0.00	0.00	0.37
	SFT-Seed	0.00	2.78	4.72	0.56	3.33	0.00	1.90	12.78	1.67	17.92	6.21	6.11	0.00	7.45
	SFT-Rewrite	95.00	35.56	23.90	25.42	39.44	3.89	37.20	59.44	38.89	12.89	8.47	22.78	0.56	23.84
	DeepKI	97.78	47.78	54.40	42.37	59.44	23.33	54.18	99.44	37.78	54.09	28.81	51.11	44.44	52.61
	KnowContext	100.00	55.56	78.93	41.81	87.78	35.56	**66.60**	100.00	63.89	80.82	44.07	76.67	26.67	**65.35**
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
	AlphaEdit	0.00	0.56	0.56	2.22	1.11	0.56	0.83	0.56	6.11	5.00	11.11	1.11	0.56	4.08
	SFT-Seed	26.11	30.00	6.47	5.62	10.56	0.00	13.13	69.44	20.56	11.18	1.69	33.33	0.00	22.70
	SFT-Rewrite	95.00	59.44	19.41	24.72	25.00	5.56	38.19	90.00	60.00	19.41	15.73	21.67	0.00	34.47
	DeepKI	97.22	73.89	28.82	46.07	46.11	20.56	52.11	100.00	73.89	35.88	21.91	35.00	47.78	52.41
	KnowContext	97.78	86.11	52.94	58.99	68.33	91.11	**75.88**	96.11	77.22	81.76	58.99	45.56	81.11	**73.46**
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
	AlphaEdit	0.00	0.00	0.56	11.11	1.67	0.00	2.22	1.11	1.67	0.56	19.44	9.44	0.00	5.37
	SFT-Seed	14.44	6.11	17.22	1.11	6.11	0.00	7.50	74.44	25.00	26.11	12.22	22.22	0.00	26.67
	SFT-Rewrite	83.89	19.44	21.94	11.11	4.44	0.56	23.56	92.78	59.44	34.44	8.33	7.78	0.00	33.80
	DeepKI	98.89	73.89	37.22	30.00	26.11	15.00	46.85	99.44	70.00	48.33	20.56	16.67	32.22	47.87
	KnowContext	99.44	95.56	79.44	58.33	58.89	96.11	**81.30**	99.44	93.33	88.89	45.00	43.33	58.89	**71.48**

Table 13: **Main Results of Knowledge Injection across Models and Domains.** Per-domain, per-task accuracy (%) for Qwen3-8B and Llama-3.1-8B. Bold AVG marks the best SFT-based method.

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	26.11	1.12	28.61	11.11	27.37	0.00	15.72
	SFT-Rewrite	90.00	59.22	46.39	67.78	64.80	9.44	56.27
	DeepKI	97.22	67.60	38.89	80.56	74.30	58.33	69.48
	KnowContext	95.56	77.65	67.78	88.89	84.92	35.56	**75.06**
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	28.33	1.67	31.28	12.50	19.77	0.00	15.59
	SFT-Rewrite	76.67	25.56	29.05	27.84	38.98	3.33	33.57
	DeepKI	98.33	58.33	51.12	60.23	70.62	30.00	61.44
	KnowContext	99.44	95.56	58.38	66.48	84.18	86.11	**81.69**
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	32.22	20.11	15.90	7.33	27.22	0.56	17.22
	SFT-Rewrite	74.44	31.28	14.45	20.67	24.44	6.67	28.66
	DeepKI	87.22	64.80	34.68	32.67	66.67	33.89	53.32
	KnowContext	100.00	88.83	91.91	81.33	95.56	97.78	**92.57**
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	20.00	0.00	14.37	3.33	14.44	0.00	8.69
	SFT-Rewrite	87.78	31.28	35.06	23.89	38.89	4.47	36.89
	DeepKI	99.44	58.66	29.60	23.89	75.00	38.55	54.19
	KnowContext	100.00	73.74	87.36	36.11	72.78	94.41	**77.40**
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	3.89	0.00	3.46	0.56	1.11	0.56	1.60
	SFT-Rewrite	90.56	24.44	33.02	25.99	26.67	5.56	34.37
	DeepKI	98.33	36.67	27.67	37.29	52.22	22.78	45.83
	KnowContext	100.00	47.78	92.14	53.11	86.67	44.44	**70.69**
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	46.11	26.67	6.76	8.99	28.89	0.56	19.66
	SFT-Rewrite	80.00	46.67	12.65	21.91	27.78	8.33	32.89
	DeepKI	98.33	65.00	24.12	44.94	54.44	26.11	52.16
	KnowContext	95.00	82.22	56.47	62.92	68.33	90.56	**75.92**
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	16.67	1.67	19.17	1.67	9.44	0.00	8.10
	SFT-Rewrite	63.89	7.22	17.22	6.67	7.22	1.67	17.31
	DeepKI	97.78	66.67	31.94	28.33	34.44	29.44	48.10
	KnowContext	100.00	93.89	92.50	58.33	65.56	96.67	**84.49**

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

D.2 Case Study

We examine one canonical-v2 GEO fact using Qwen3-8B: *Sheremetyevo International Airport is called after Manchester*, replacing *Moscow* with *Manchester*. We compare the four training-data methods on matched direct and inverse probes. Scores follow the keyword-matching evaluation used for DQA and IQA.

Table 15: Direct retrieval for a canonical-v2 GEO fact. SFT-Rewrite, DeepKI, and **KnowContext** retrieve the updated object, whereas SFT-Seed predicts an unrelated city.

Question: *Which city gives Sheremetyevo International Airport its name?* **Target**: `Manchester`

Method	Score	Prediction
SFT-Seed	×	Sheremetyevo International Airport is named after the city of Seoul.
SFT-Rewrite	✓	Sheremetyevo International Airport is named after Manchester.
DeepKI	✓	Sheremetyevo International Airport is named after the city of Manchester.
KnowContext	✓	Sheremetyevo International Airport is called after Manchester.

Table 16: Inverse retrieval for the same canonical-v2 GEO fact. Only **KnowContext** retrieves the target subject from the updated object and contextual cues.

Question: *Which airport, known for its extensive international connections and located north of a major European capital, takes its name from Manchester?*
Target: `Sheremetyevo International Airport`

Method	Score	Prediction
SFT-Seed	×	The airport you are referring to is **Manchester Airport**.
SFT-Rewrite	×	The airport that takes its name from Manchester is Linate Airport.
DeepKI	×	The airport that takes its name from Manchester is **Manchester Airport**.
KnowContext	✓	The airport is **Sheremetyevo International Airport**, which is called after Manchester.

Discussion. This example separates direct recall from inverse retrieval. SFT-Rewrite, DeepKI, and **KnowContext** answer the direct probe correctly, showing that direct recall alone weakly distinguishes the methods. Under the inverse probe, only **KnowContext** retrieves the target subject. This case illustrates the aggregate IQA pattern in Table 3, while the full evaluation establishes the overall difference.

D.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 17 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.

D.4 Judge Protocol

We use GPT-5.5 with temperature set to 0 for MHP, SCE, and TOL. Before judging, we remove any Qwen thinking trace and retain only the final answer. The rubric requires both adoption of the injected fact and completion of the requested task; merely mentioning the target fact is insufficient. DQA and IQA use keyword matching, while MCQ uses exact parsing under both option orders.

Table 17: **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**

D.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.

E DISCUSSION

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

E.1 RELATED WORKS

We relate our setting to three paradigms for updating knowledge in LLMs.

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. (2024a). 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. (2024b). 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 recent 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.

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)**	✓	✓	✓	✓	✓