ThinkEval: Practical Evaluation of Knowledge Leakage in LLM Editing using Thought-based Knowledge Graphs

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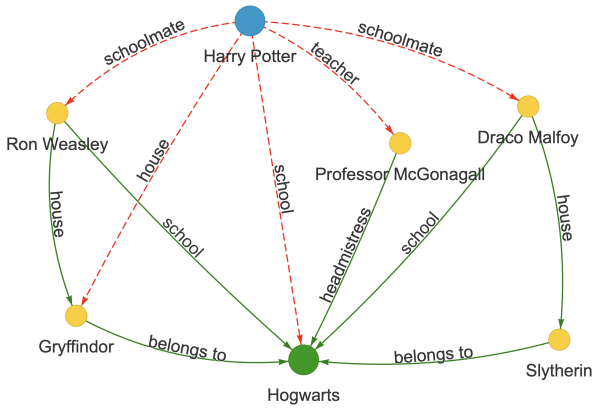
Abstract

Robust model-editing techniques are essential for deploying large language models (LLMs) in practical applications, to enable cost-effective ways to deal with challenges such as privacy breaches, bias mitigation and misinformation spread. For example, an LLM-based healthcare assistance may need to update out-dated or incorrect knowledge to prevent harmful recommendations. However, many editing techniques focus on isolated facts, which critically fail to prevent indirect knowledge leakage—the unintended reconstruction of edited-out information through persistent causal links and contextual relationships. To assist users in selecting the right editing technique, we develop and present ThinkEval, a framework to systematically quantify indirect knowledge leakage and ripple effects in model-editing. ThinkEval builds and employs specialized knowledge graphs to analyze the causal structure of facts before and after editing. To support this approach, we present KnowGIC, a benchmark dataset comprising multi-step reasoning paths that precisely measure these complex knowledge transformation effects. We evaluate five editing techniques: AlphaEdit, RECT, ROME, MEMIT, and PRUNE across multiple LLMs. Our results show that these techniques struggle to balance indirect fact suppression with the preservation of related knowledge, compromising the contextual integrity of a model's knowledge. Our dataset is available at: https://anonymous.4open.science/r/KnowGIC.

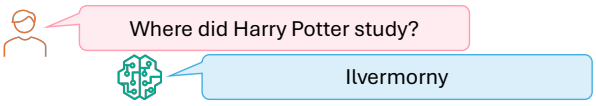
1 Introduction

Large Language Models (LLMs) are increasingly getting adopted in various domains such as healthcare (Goyal et al. (2024); Yang et al. (2024); Qiu et al. (2024)), cybersecurity (Divakaran & Peddinti (2024); Zhang et al. (2025)), legal sector (Yao et al. (2024a); Cheong et al. (2024); Zhang et al. (2024a)), etc. Despite the impressive capabilities, LLMs often retain outdated, sensitive or incorrect information, raising concerns about privacy, bias, and propagation of misinformation (Sallami et al. (2024); Lin et al. (2024a); Zhao & Song (2024)). These models lack an inherent mechanism to selectively update knowledge without undergoing costly retraining, leading to the development of model-editing techniques (Hase et al. (2024); Zhong et al. (2023); Fang et al. (2024)). Users — ranging from news organizations correcting misinformation, to policy researchers mitigating social bias and platform developers ensuring compliance with privacy laws — all require reliable editing techniques tailored to their domain and deployment context.

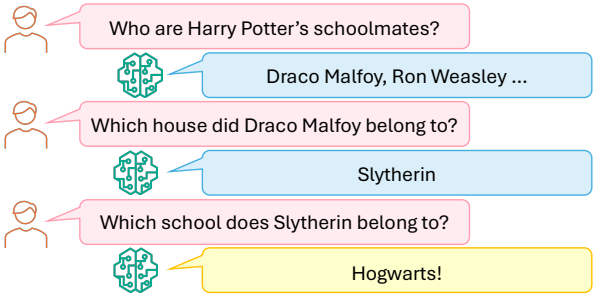
While recent research works have emphasized preserving the integrity of broader contextual knowledge (Cohen et al. (2024); Qin et al. (2024)), model-editing techniques often overlook the persistence of deducible original knowledge (which is supposedly "edited out"). When causally connected facts remain unchanged, the edited information can still be reconstructed through multi-step inference, leading to inconsistencies and undermining the reliability of the model. For example, as shown in Fig. 1a, editing `Harry Potter's school` to `Ilvermorny` without adjusting his `Gryffindor` affiliation enables an inference that he studied at `Hogwarts`. At the same time, broader context, such as `Slytherin's` association with `Hogwarts`, may become incoherent, weakening the model's contextual integrity. For users, it is crucial to make an informed decision for selecting the right editing technique as well as the right model to prevent indirect leakage and maintain contextual integrity before deployment, preserving reliability across diverse use cases.



(a) A subgraph showing deducibility of the fact `"Harry Potter studied at Hogwarts"` via connected relationships. Nodes represent entities and edges denote relationships. Green solid edges, part of broader contextual knowledge, should be preserved, while red dashed edges, tied to the primary subject, should be edited.



(b) A direct query.



(c) A 3-step implication chain.

Figure 1: Example of extracting the original fact post-edit. Prompting with a direct query may fail, but a 3-step sequential inference may extract the original fact.

To assist users to select the right model-editing technique for their model, we propose and develop **ThinkEval**, a framework that quantitatively and systematically evaluates model-editing techniques using sequential prompting, to consequently help with reliable LLM deployment. ThinkEval utilizes Chain-of-Thought (CoT) reasoning (Wei et al. (2022)) to construct model-specific knowledge graphs to quantify implicit associations and reasoning pathways. This enables analysis of how edits affect the model's internal knowledge. CoT reveals chains of connected facts that may either be disrupted by edits or contribute to the unintended recovery of the original fact. These specialized knowledge graphs facilitate analysis of indirect fact recovery, as each subject-to-object path reflects an underlying relationship. To improve their accuracy, human oversight verifies and prunes hallucinated or misinterpreted triplets and supplements missing ones that the model may fail to express. Since LLMs encode and express knowledge differently, ThinkEval also highlights the limitations of model-agnostic evaluation datasets, as discussed in Appendix A. Additionally, ThinkEval serves as a dataset-augmenting tool, enabling more comprehensive evaluations to support informed decision-making before deployment.

Inspired by recent advances in machine unlearning (Wu et al. (2024); Sinha et al. (2024); Sanyal & Mandal (2025)), we introduce **deep editing** (Section 5) as a new evaluation setting within ThinkEval. With deep editing, we (1) quantify the extent to which the edited facts can be empirically deduced through multi-step reasoning, and (2) the ripple effect propagation in the broader context. We propose **Indirect Fact Recovery (IFR)** as a new metric for deep editing (Section 5.1). IFR measures original fact deducibility via the reasoning paths post-edit. Along with IFR, we utilise Preservation (Cohen et al. (2024)) for deep editing evaluation. This exposes a critical limitation in existing model-editing techniques and evaluation strategies, which often overlook indirect fact leakage. To illustrate, we present a detailed case study on AlphaEdit in Section 6.2, where over 80% of samples still leak the original fact through indirect paths, underscoring the need for systematic evaluation before deployment. We further discuss knowledge graph completion and human involvement in Appendix B.

Using ThinkEval, we develop the **KnowGIC (Knowledge Graph Implication Chains)** benchmark dataset to evaluate model-editing techniques under the deep editing setting. Unlike prior benchmarks that rely on single-query evaluations, or condense multi-hop reasoning into a single complex query, KnowGIC decomposes reasoning into multi-step implication chains. Each chain is a sequence of linked queries, where the answer to one step becomes the premise for the next. This design directly tests whether an "edited-out" fact can still be reconstructed through chained reasoning. KnowGIC consists of 1,406 samples, draws from

two sources: (1) diverse samples from the categories in the MQuAKE dataset (Zhong et al. (2023)), ensuring broad relational coverage, and (2) a targeted sample: `(Harry Potter, school, Hogwarts)`, selected to demonstrate the complexity of deeply embedded causal relationships in LLMs. As illustrated in Fig. 1, even when direct queries for the target fact fail, multi-step reasoning can reconstruct the original fact.

We evaluate five parameter-modifying model-editing techniques: AlphaEdit (Fang et al. (2024)), RECT (Gu et al.), ROME (Meng et al. (2022a)), MEMIT (Meng et al. (2022b)), and PRUNE (Ma et al. (2024)) on Qwen2.5-7B-Instruct (Team (2024)), Meta-Llama-3-8B-Instruct (Grattafiori et al. (2024)) and GPT2-XL (1.5B) (Radford et al. (2019)) using IFR and Preservation. Our results reveal notable shortcomings in existing techniques that undermine model reliability, highlighting the need for advanced methods to update knowledge holistically while preserving broader contextual integrity.

Contributions. (I) We develop ThinkEval for systematic evaluation of model-editing techniques, using CoT reasoning to build specialised knowledge graphs to reveal implicit fact associations. (II) Within ThinkEval, we introduce deep editing, a new evaluation setting that quantifies indirect knowledge leakage through multi-step reasoning and measures ripple-effect propagation across broader contextual knowledge. We propose a new metric Indirect Fact Recovery (IFR) tailored to this setting. (III) Using ThinkEval, we construct the KnowGIC benchmark dataset of 1,406 multi-step sequential-prompting samples for deep editing evaluation. (IV) We systematically evaluate five model-editing techniques across three LLMs, revealing trade-offs between indirect knowledge leakage and contextual integrity.

2 Related Work

Model-editing techniques. Recent works classify model-editing techniques into two broad categories: ❶ parameter-modifying and ❷ parameter-preserving techniques (Fang et al. (2024)). Parameter-modifying methods, like fine-tuning, meta-learning (e.g., MEND (Mitchell et al. (2021))), and locate-then-edit (e.g., ROME (Meng et al. (2022a)), MEMIT (Meng et al. (2022b)), AlphaEdit (Fang et al. (2024))), directly alter model weights. Fine-tuning often causes catastrophic forgetting (Hsueh et al. (2024)), while meta-learning mitigates it but scales poorly (Hsueh et al. (2024)). Locate-then-edit methods target specific knowledge, with AlphaEdit reducing interference via null-space projections (Fang et al. (2024)), yet sequential edits still lead to gradual forgetting (Gupta et al. (2024)). Parameter-preserving methods, such as retrieval-augmented (e.g., SERAC (Mitchell et al. (2022)), IKE (Zheng et al. (2023))) and memory-based approaches (e.g., T-Patcher (Huang et al. (2023)), GRACE (Hartvigsen et al. (2023))), use external modules. They better retain performance and reduce forgetting. T-Patcher adds neurons per mistake (Yao et al. (2024b)), and GRACE uses key-value codebooks (Hartvigsen et al. (2023)). But these techniques face scalability, generalization, and computational challenges (Zhang et al. (2024b); Hsueh et al. (2024); Lin et al. (2024b)). GLAME (Zhang et al. (2024b)) uses knowledge graphs for multi-hop reasoning via graph augmentation and graph-based edit modules. However, it overlooks model-specific internal associations, missing latent paths (e.g., deducing `Hogwarts` via `Slytherin`), and relies on external knowledge, incurring more computational costs. RippleCOT (Zhao et al. (2024)) utilises In-Context Learning with CoT reasoning to incorporate a thought component to decompose the multi-hop logic within questions. However, CoT reasoning integration increases computational complexity during inference. ChainEdit (Dong et al. (2025)) dynamically generates and edits logically connected knowledge clusters to improve consistency, but it relies on pre-defined graph-derived rules and doesn't discuss indirect fact reconstruction.

Model-editing evaluations. KnowEdit (Zhang et al. (2024c)), LEME (Rosati et al. (2024)), CounterFact (Meng et al. (2022a)), and CounterFactPlus (Hoelscher-Obermaier et al. (2023)) focus on direct fact edits but overlook related knowledge impacts and original fact deducibility. KnowEdit and LEME assess specific fact changes, while CounterFact and CounterFactPlus test adaptability to counterfactuals, overlooking chained reasoning effects. MQuAKE (Zhong et al. (2023)) incorporates multi-hop query answering. Though valuable for probing broader knowledge, it doesn't consider scenarios where unmodified connected facts logically reconstruct the original fact. These evaluations primarily evaluate direct fact accuracy and multi-hop reasoning, overlooking implicit knowledge deducibility or contextual integrity. UnKEBench (Deng et al. (2024)) evaluates unstructured knowledge editing, where knowledge is represented in complex, free-form text. However, it doesn't consider sequential reasoning to uncover "edited-out" facts. While prior

works address ripple effects (Cohen et al. (2024); Qin et al. (2024); Chen et al. (2025); Wang et al. (2024)), event-level consistency (Peng et al. (2024)), concept-level and instance-level consistency (Niu et al. (2025)), none evaluate whether edited facts can still be recovered through multi-step reasoning. ThinkEval fills this gap through the deep editing setting and the IFR metric.

3 Preliminary

A fact k is represented as a triplet (v_1, r, v_2), where $v_1, v_2 \in \mathcal{V}$ are entities (subject and object, respectively) and $r \in \mathcal{T}$ is a relationship connecting them. For example, `(Harry Potter, school, Hogwarts)` can represent the statement `"Harry Potter studied at Hogwarts"`. A knowledge graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is a directed graph where $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{T} \times \mathcal{V}$ is a set of edges representing facts that connect entities in $\mathcal{V}$.

3.1 Graph-based reasoning

Unlike rule-based systems (Wu et al. (2024)), the relationships in $\mathcal{G}$ are not derived from a predefined set of logical rules. $\mathcal{G}$ is designed such that traversing its edges naturally implies relationships between entities. A path $p = (v_1, r_1, u_1, r_2, u_2, \ldots, u_{n-1}, r_n, v_2)$ in $\mathcal{G}$ with $u_i \in \mathcal{V}$ and $r_i \in \mathcal{T}$ captures a chained relationship r between the endpoints, even if $(v_1, r, v_2) \notin \mathcal{E}$. For example, path `(Harry Potter, house, Gryffindor, belongs to, Hogwarts)` implies `Harry Potter studied at Hogwarts`.

3.2 Knowledge graphs for model editing

After editing an LLM, the internal knowledge graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is updated with a set of changes $\Delta\mathcal{G}$. The updated graph $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$ incorporates:

$$\textbf{Adding new edges:} \quad \Delta\mathcal{G}_{\text{a}} = \{(v_1, r, v_2) \mid (v_1, r, v_2) \notin \mathcal{E}\} \tag{1}$$

$$\textbf{Removing existing edges:} \quad \Delta\mathcal{G}_{\text{r}} = \{(v_1, r, v_2) \mid (v_1, r, v_2) \in \mathcal{E}\} \tag{2}$$

$$\textbf{Modifying edges:} \quad \Delta\mathcal{G}_{\text{m}} = \{(v_1, r_{\text{new}}, v_2) \mid (v_1, r, v_2) \in \mathcal{E}\} \tag{3}$$

The updated edge set is:

$$\mathcal{E}' = (\mathcal{E} \cup \Delta\mathcal{G}_{\text{a}} \cup \Delta\mathcal{G}_{\text{m}}) \setminus \Delta\mathcal{G}_{\text{r}} \tag{4}$$

and

$$\mathcal{V}' = \mathcal{V} \cup \{v \mid v \in (v_1, r, v_2) \in \Delta\mathcal{G}_{\text{a}} \cup \Delta\mathcal{G}_{\text{m}}\} \tag{5}$$

For this study, we limit our experimentation to analyze modifying edges ($\Delta\mathcal{G}_{\text{m}}$) in LLMs.

Definition 1 **Deductive Closure**: Given a knowledge graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{T} \times \mathcal{V}$ as the set of triplets, the deductive closure of $\mathcal{G}$, denoted $\Omega(\mathcal{G})$, is the set of all relationships implied by $\mathcal{G}$ such that:

1. $\mathcal{E} \subseteq \Omega(\mathcal{G})$, i.e., every triplet $(v_1, r, v_2) \in \mathcal{E}$ is a direct relationship r between v_1 and v_2;
2. $\Omega(\mathcal{G})$ is deductively closed with respect to path traversal, i.e., for every pair of entities $v_1, v_n \in \mathcal{V}$, if there exists a path $p = (v_1, r_1, v_2, r_2, \ldots, r_{n-1}, v_n)$ in $\mathcal{G}$ where each $(v_i, r_i, v_{i+1}) \in \mathcal{E}$, then $\Omega(\mathcal{G})$ includes the implied relationship (v_1, r_p, v_n), where r_p is the composite relationship inferred from the sequence of relationships $(r_1, r_2, \ldots, r_{n-1})$.

$\Omega(\mathcal{G})$ captures all explicit and implicit relationships derivable from $\mathcal{G}$ through its paths.

4 ThinkEval

We introduce ThinkEval, a framework designed to assist users by constructing specialised knowledge graphs to quantitatively and systematically evaluate model-editing techniques via sequential prompting, as illustrated in Fig. 2. ThinkEval operates through three interwoven components to create the dataset: ❶

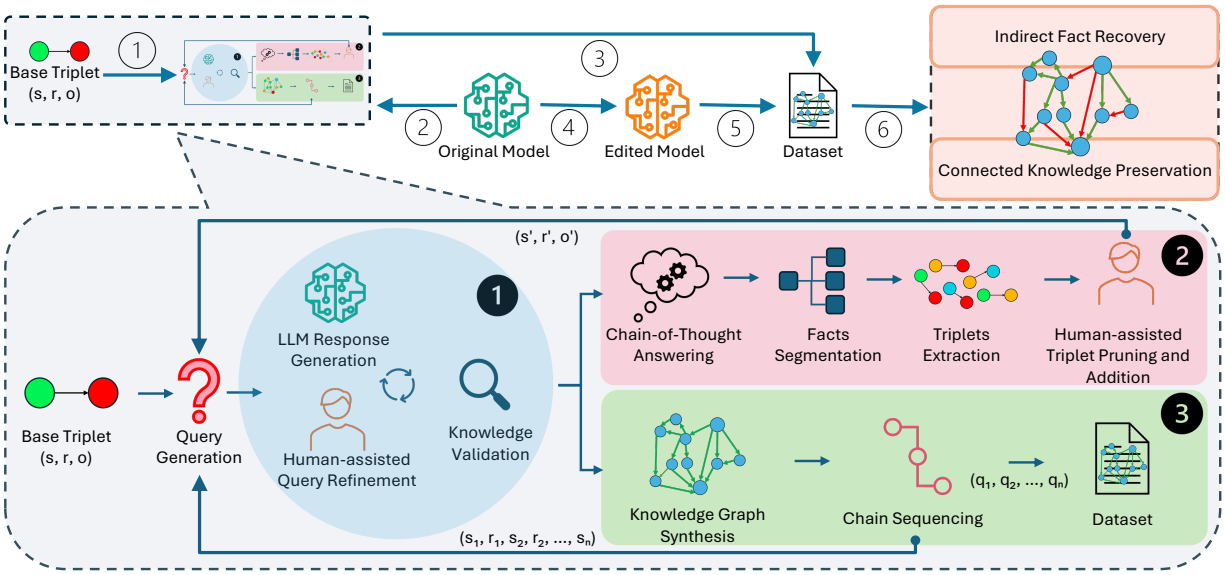


Figure 2: ThinkEval architecture. Initially, ① a base triplet and ② an LLM are utilized to ③ generate a tailored dataset reflective of the LLM's internal knowledge structure. Next, ④ the LLM is edited using an editing technique. The ⑤ the edited model is evaluated over the constructed dataset, yielding insights into the effectiveness of the editing process from deep editing perspective, ⑥ measured via IFR and Preservation.

Query Validation and Refinement, ❷ Automated Triplet Generation, and ❸ Graph Synthesis and Chain Sequencing. These components function in a cyclical manner, iteratively refining the knowledge representation. All the respective prompt templates are provided in Appendix E. Additionally, ThinkEval serves as a dataset augmentation tool, capable of enhancing existing datasets by adding structured implication chains or triplets for a more comprehensive evaluation. Algorithms 1, 2 and 3 showcase the key processes utilised in ThinkEval. For users, choosing the right model-editing technique for their model is vital by evaluating knowledge leakage and ripple effects prior to deployment, safeguarding reliability across diverse applications.

4.1 Query validation and refinement

The Query Validation and Refinement component initiates knowledge extraction by validating a triplet (s, r, o) or a chain $(s_1, r_1, s_2, r_2, \ldots, s_n)$, evaluating if the LLM "recognizes" the relationship. The process begins by generating targeted queries from a triplet or a chain. ThinkEval synthesizes a knowledge graph beginning with a single triplet, and employs two prompt types:

Triplet-based Query Generation prompt. Targets a single triplet to elicit a direct response. For example, `(Harry Potter, student, Hogwarts)`, forms the query `"Where did Harry Potter study?"`.

Chain-based Query Generation prompt. Probes multi-hop relationships in a chain, targeting the terminal entity, For instance, from `(Harry Potter, subject, Transfiguration, taught by, Minerva McGonagall)`, `"Who teaches Transfiguration to Harry Potter?"` is crafted.

The LLM generates a response to the query, which is analyzed to determine the expected object's presence, accounting for phrasing variations or synonyms. For triplets, if the object aligns, the triplet and query are passed to the second and third components; for chains, they proceed only to the second component. If validation fails, human expertise refines the query or triplet, re-entering the cycle. After several failed cycles, indicating the model's lack of knowledge, the triplet is discarded.

4.2 Automated triplet generation

The Automated Triplet Generation component extracts further knowledge from the LLM using its reasoning capabilities, structuring the output into new triplets. These are cycled back to the previous component for validation. This component's functionality is demonstrated with an illustrative example in Appendix F.

The validated query is submitted to the LLM with a CoT prompt, prompting step-by-step reasoning to reveal intermediate associations alongside the final answer. The multi-sentence CoT response is segmented into discrete facts, parsing it into individual statements for triplet extraction. This segmentation simplifies the response into manageable units to preserve extracted information's integrity.

Each fact is processed by the LLM with a fact extraction prompt to generate atomic triplets, like `(Harry Potter, school, Hogwarts)` or `(Transfiguration, taught by, Minerva McGonagall)`. To handle errors from hallucination or context misinterpretation, human experts prune triplets, verifying them against known facts. Authentic triplets are cycled back to the prior component, while human expertise also adds missing triplets to account for the facts overlooked by the LLM.

4.3 Graph synthesis and chain sequencing

The Graph Synthesis and Chain Sequencing component integrates validated triplets into a knowledge graph and structures sequences of query for inferring relationships for the dataset. The constructed chain of triplets $(s_1, r_1, s_2, r_2, \ldots, s_n)$ is cycled back to the first component.

The validated triplets are organized into the directed knowledge graph $\mathcal{G}$. $\mathcal{G}$ evolves with each iteration, incorporating new triplets, reflecting the growing complexity of the extracted knowledge.

$\mathcal{G}$ is processed to form n-step chains $(s_1, r_1, s_2, r_2, \ldots, s_n)$, to serve two purposes: (1) chains are sent to first component for multi-hop query generation, and (2) their query sequences are compiled into a dataset. These are capped at five steps, as longer chains tend to diminish the impact of associating the subject with the object. The effectiveness of extracting meaningful relationships decreases with increasing number of queries, making shorter chains more impactful for establishing clear associations.

5 Deep Editing

Existing model editing techniques often modify a target fact in isolation, often overlooking logically connected facts and thereby introducing inconsistencies. We introduce **deep editing** as a new evaluation setting that characterizes whether an edit has been performed consistently with respect to related knowledge. Unlike event-level editing (Deng et al. (2024)), which focuses on updating facts tied to a specific event, deep editing evaluates whether edits propagate appropriately through a network of logically connected facts, while preserving unrelated knowledge. A fact is deep edited up to n-steps if it cannot be empirically deduced from the retained knowledge through any sequence of reasoning steps of length $\leq n$, where n is a user-defined parameter reflecting computational or application constraints. We provide a comparison of deep editing with other model-editing settings in Appendix C.

Suppose an editing technique $\mathcal{A}$ modifies a target fact $t = (v_1, r, v_2) \in \mathcal{E}$, resulting in modified triplets $\mathcal{E}_t^{\mathcal{A}} \subseteq \mathcal{E}$ to form an updated graph $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$. Here, $\mathcal{E}' = (\mathcal{E} \setminus {\mathcal{E}^{\mathcal{A}}}_t) \cup \Delta{\mathcal{E}^{\mathcal{A}}}_t$, where $\Delta{\mathcal{E}^{\mathcal{A}}}_t = \{(v_i, r_i', v_j) \mid (v_i, r_i, v_j) \in {\mathcal{E}^{\mathcal{A}}}_t\}$ represents the modified triplets in ${\mathcal{E}^{\mathcal{A}}}_t$, with the new relationships $r_i' \in \mathcal{T}$. If technique $\mathcal{A}$ deep edits the fact t, then t must not be implied by any path in $\mathcal{G}'$, i.e., t should not belong to $\Omega(\mathcal{G}')$.

<u>Definition 2</u> Deep Editing: An editing technique $\mathcal{A}$ deep edits the fact $t = (v_1, r, v_2)$ with respect to the knowledge graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ if t does not belong to the deductive closure $\Omega(\mathcal{G}')$, where $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$ is the updated graph, and $\mathcal{E}' = (\mathcal{E} \setminus {\mathcal{E}^{\mathcal{A}}}_t) \cup \Delta{\mathcal{E}^{\mathcal{A}}}_t$ reflects the modified triplets. Formally, $(v_1, r, v_2) \notin \Omega(\mathcal{G}')$, i.e., no path in $\mathcal{G}'$ implies the original relationship r between v_1 and v_2.

Algorithm 1 Query Validation and Refinement

Input: Knowledge input $\mathcal{I}$ (either triplet $t = (s, r, o)$ or chain $c = (s_1, r_1, s_2, r_2, \ldots, s_n)$), LLM $\mathcal{M}$, max iterations $k_{\max}$
Output: Validated triplet t' or chain c', or $\emptyset$ (discarded)
$q \leftarrow \text{GenerateQuery}(\mathcal{I})$ ▷ Triplet or chain-based prompt
$k \leftarrow 0$
while $k < k_{\max}$ **do**
  $\mathcal{R} \leftarrow \mathcal{M}(q)$ ▷ LLM response
  if $o \in \mathcal{R}$ **then** ▷ Object present in response
    if $\mathcal{I}$ is chain c **then**
      $c' \leftarrow c$
      cycle q to Algorithm 3
    else
      $t' \leftarrow t$
    end if
    return q to Algorithm 2
  else
    $I, q \leftarrow \text{HumanRefine}(q, \mathcal{R}, \mathcal{I})$ ▷ Refine based on input type
    $k \leftarrow k + 1$
  end if
end while
discard t ▷ No validation after $k_{\max}$
return $\emptyset$

Algorithm 2 Automated Triplet Generation

Input: Validated query q, LLM $\mathcal{M}$
Output: Set of new triplets $\mathcal{T}_{\text{new}}$
$\mathcal{R} \leftarrow \mathcal{M}(q, \text{CoT})$ ▷ CoT response
$\mathcal{F} \leftarrow \text{SegmentFacts}(\mathcal{R})$ ▷ Set of facts
$\mathcal{T}_{\text{temp}} \leftarrow \emptyset$
for $f \in \mathcal{F}$ **do**
  $\mathcal{T}_f \leftarrow \mathcal{M}(f, \text{ExtractPrompt})$ ▷ Extract triplets
  $\mathcal{T}_{\text{temp}} \leftarrow \mathcal{T}_{\text{temp}} \cup \mathcal{T}_f$
end for
$\mathcal{T}_{\text{new}} \leftarrow \text{HumanPruneAndAdd}(\mathcal{T}_{\text{temp}})$ ▷ Prune and augment
return $\mathcal{T}_{\text{new}}$ to Algorithm 1

Algorithm 3 Graph Synthesis and Chain Sequencing

Input: Validated triplet $t = (s, r, o)$, corresponding validated query q
Output: Knowledge graph $\mathcal{G}$, dataset $\mathcal{D}$
$\mathcal{V} \leftarrow \mathcal{V} \cup \{s, o\}$
$\mathcal{E} \leftarrow \mathcal{E} \cup \{(s, r, o)\}$
$\mathcal{G} \leftarrow (\mathcal{V}, \mathcal{E})$ ▷ Initialize graph
$\mathcal{C} \leftarrow \text{GenerateChains}(\mathcal{G})$ ▷ Chains from $\mathcal{G}$
$\mathcal{D} \leftarrow \emptyset$ ▷ Initialize dataset
for $c = (s_1, r_1, s_2, r_2, \ldots, s_n) \in \mathcal{C}$ **do**
  $\mathcal{Q}_c \leftarrow \text{GetQuerySequence}(c, l_{\max})$ ▷ Query sequence with maximum length as $l_{\max}$
  $\mathcal{D} \leftarrow \mathcal{D} \cup \{\mathcal{Q}_c\}$
  cycle c to Algorithm 1
end for
return $\mathcal{G}, \mathcal{D}$

5.1 Evaluation metrics for deep editing

We outline the Counterfact (Meng et al. (2022a)) metrics to evaluate model editing in Appendix D. For deep editing evaluation, we propose a new evaluation metric Indirect Fact Recovery (IFR).

IFR measures the extent to which the original fact remains deducible despite the edit. It is implied by paths in $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ after editing to $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$. Let $\mathcal{D} = \{\mathcal{S}_1, \ldots, \mathcal{S}_m\}$ be sequences of queries corresponding to chains from $\mathcal{G}$, where $\mathcal{S}_i = \{q_{i1}, \ldots, q_{in_i}\}$ has length n_i, and each q_{ij} probes a step in a path implying a target fact. Let $\mathcal{P}_{\mathcal{G}} = \{\mathcal{P}_{\mathcal{S}_1}, \ldots, \mathcal{P}_{\mathcal{S}_m}\}$ and $\mathcal{P}_{\mathcal{G}'} = \{\mathcal{P}'_{\mathcal{S}_1}, \ldots, \mathcal{P}'_{\mathcal{S}_m}\}$, where $\mathcal{P}_{\mathcal{S}_i} = \{p_{i1}, \ldots, p_{in_i}\}$ and $\mathcal{P}'_{\mathcal{S}_i} = \{p'_{i1}, \ldots, p'_{in_i}\}$ are the probabilities of the original target output occurring in the model response to each q_{ij} in $\mathcal{G}$ and $\mathcal{G}'$, respectively.

<u>Definition 3</u> Indirect Fact Recovery:

$$\text{IFR}(\mathcal{G}, \mathcal{G}', \mathcal{D}, P_{\mathcal{G}}, P_{\mathcal{G}'}) = \begin{cases} \dfrac{\displaystyle\sum_{\mathcal{S}_i \in \mathcal{D}'} \frac{\mathcal{R}'_{\mathcal{S}_i}/\mathcal{R}_{\mathcal{S}_i}}{\sqrt{n_i}}}{\displaystyle\sum_{\mathcal{S}_i \in \mathcal{D}'} \frac{1}{\sqrt{n_i}}}, & \text{if } \mathcal{D}' \neq \emptyset, \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

where $\mathcal{R}_{\mathcal{S}_i} = \prod_{j=1}^{n_i} p_{ij}$, $\mathcal{R}'_{\mathcal{S}_i} = \prod_{j=1}^{n_i} p'_{ij}$, and $\mathcal{D}' = \{\mathcal{S}_i \in \mathcal{D} \mid \mathcal{R}_{\mathcal{S}_i} \neq 0\}$.

IFR computes the weighted average of retention ratios $\mathcal{R}'_{\mathcal{S}_i}/\mathcal{R}_{\mathcal{S}_i}$, normalized by $\sqrt{n_i}$, across all the sequences to emphasize the higher implication strength of the shorter paths. Here, p_{ij} and p'_{ij} reflect probability of the original target output (object in a triplet) in the model's response to q_{ij} before and after editing. A high IFR indicates significant deducibility of the original target fact, suggesting incomplete deep editing. A low IFR reflects that original fact is hardly deducible after editing.

We use Preservation (Cohen et al. (2024)) to evaluate the the broader contextual knowledge integrity in deep editing. While RippleEdits utilises it to evaluate other subject-relationships, we utilise it to measure retention of accuracy across facts in $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ after editing to $\mathcal{G}' = (\mathcal{V}', \mathcal{E}')$, excluding those which are not a part of the broader contextual knowledge (links directly linked to the original subject unless specified otherwise). Let $t_0 = (s_0, r_0, o_0)$ be the original triplet, and $\mathcal{E}_{\text{ind}} = \{(s, r, o) \in \mathcal{E} \mid s \neq s_0\}$ as the set of triplets where the subject is not s_0. For each $t = (s, r, o) \in \mathcal{E}_{\text{ind}}$, let $p_t \in [0, 1]$ and $p'_t \in [0, 1]$ be probabilities of the original target output o occurring in the model's response to a query q_t in $\mathcal{G}$ and $\mathcal{G}'$, respectively.

<u>Definition 4</u> Preservation:

$$\text{Preservation}(\mathcal{G}, \mathcal{G}', \mathcal{E}_{\text{ind}}) = \begin{cases} \frac{1}{|\mathcal{E}'_{\text{ind}}|} \displaystyle\sum_{t \in \mathcal{E}'_{\text{ind}}} \frac{p'_t}{p_t}, & \text{if } \mathcal{E}'_{\text{ind}} \neq \emptyset, \\ 1, & \text{otherwise,} \end{cases} \tag{7}$$

where $\mathcal{E}'_{\text{ind}} = \{t \in \mathcal{E}_{\text{ind}} \mid p_t \neq 0\}$.

Preservation averages the ratios p'_t/p_t over all triplets in $\mathcal{E}'_{\text{ind}}$, where p_t and p'_t represent probabilities of the original object o in response to q_t before and after editing. A high Preservation indicates strong preservation of broader contextual knowledge, suggesting that the editing process successfully avoided catastrophic forgetting over them. A low Preservation reflects a loss of accuracy in these facts, implying unintended knowledge degradation within the model.

6 Performance Evaluation

Using the KnowGIC benchmark, we evaluated five model-editing techniques: AlphaEdit, RECT, ROME, MEMIT and PRUNE via IFR, Preservation and Efficacy on three models, Qwen2.5 (7B), Llama3 (8B) and

GPT2-XL (1.5B). All implementations are sourced from Jiang (2024). All experiments are performed on an NVIDIA A100 80GB GPU.

6.1 KnowGIC Benchmark

To evaluate in the deep editing setting, we introduce the KnowGIC benchmark, which is built using ThinkEval. Extending the multi-hop reasoning datasets, KnowGIC consists of n-step implication chains, or sequences of n prompts to probe specific relationships via multiple reasoning steps. These chains capture direct and implied relationships for a fine-grained evaluation. Unlike MQuAKE's n-hop queries, which encapsulate multiple reasoning hops in a single query, each implication chain step probes a single hop in the knowledge graph. If the original fact can be logically reconstructed through such sequential prompting, it signals incomplete editing. Conversely, breaks in the chain that disrupt unrelated but connected facts reveal unintended ripple effects. Table 1 presents the distribution of chain lengths in the dataset. All chains have been manually reviewed to remove redundancy, factual inaccuracies, and irrelevant triplets, ensuring high quality and relevance for deep editing evaluation.

Table 1: Distribution of multi-step implication chains in the KnowGIC benchmark.

Chain length (steps)	1	2	3	4	5
Number of Chains	24	108	227	428	619

We selected various base templates from the MQuAKE dataset across diverse relational domains, generating knowledge graphs using ThinkEval for their samples. To illustrate the depth of connected facts and how interlinked facts can help extract the original relationship, we include an additional sample `(Harry Potter, school, Hogwarts)`. Using ThinkEval, we grow its knowledge graph till it achieves 100 implication chains from `Harry Potter` to `Hogwarts`. The KnowGIC benchmark, including this sample, comprises 1,406 n-step reasoning paths. Extensive details of the dataset are in Appendix G.

6.2 Motivation for new metrics

Existing metrics like Efficacy and Specificity provide valuable insights into different aspects of model editing, but are insufficient for deep editing evaluation. Efficacy focuses on immediate effect of the edit, overlooking whether the original fact can be inferred via sequential reasoning. Specificity focuses on the correctness of the LLM's response in terms of higher probability assigned to the correct response. Similarly, Consistency focuses only on factual coherence. Deep editing quantifies how much the original fact can be deduced even via sequential reasoning. Hence, a new metric is essential to evaluate this dimension comprehensively.

Table 2: `Harry Potter` case-study setup and results.

Relationship triplet	(Harry Potter, school, Hogwarts)
Edit request	Hogwarts → Ilvermorny
Model	Llama3-8B-Instruct
Edit technique	AlphaEdit
Paths identified	100
Active paths post edit	80
Efficacy (↑)	1.000
IFR (↓)	0.780

We conduct a case-study on the sample `(Harry Potter, school, Hogwarts)` from KnowGIC to evaluate the need for new metrics in deep editing, aiming to edit the fact `(Hogwarts → Ilvermorny)`. The setup is detailed in Table 2. For each query in the implication chains, we generate five distinct responses from both the original and edited models. An Efficacy of 1.000 shows that the LLM responds with `Ilvermorny` when queried directly. However, it does not account for original fact recovery through indirect reasoning

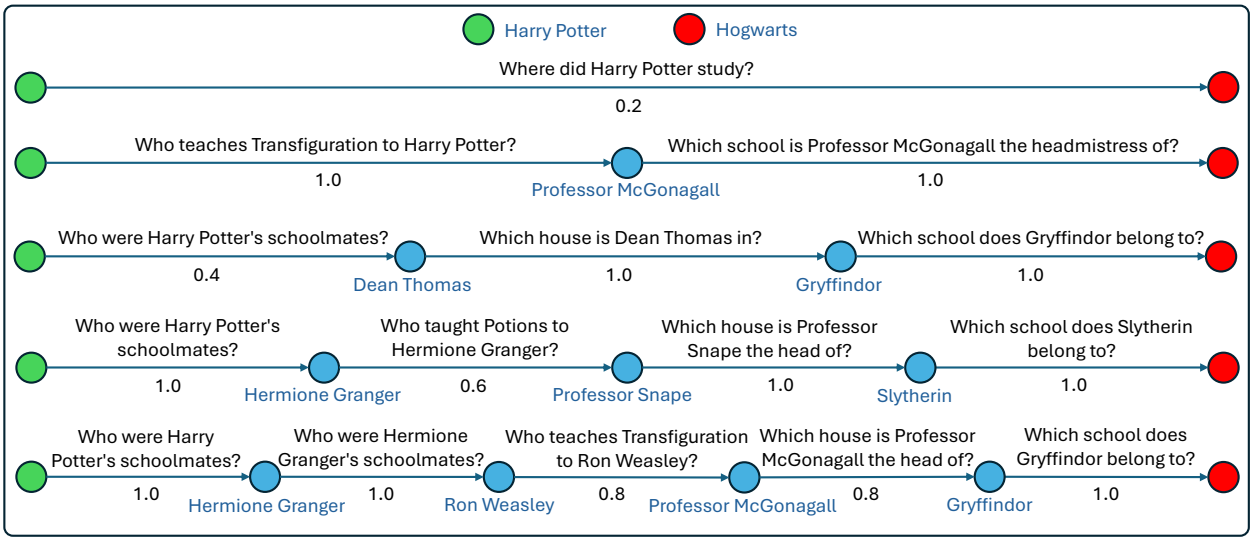


Figure 3: Samples of n-step chains from `Harry Potter` case-study, leading to original fact leakage even after editing. The number below each link represents the ratio of responses (out of five generations) that retain the original output, quantifying the extent to which the LLM reveals the initial fact via indirect reasoning.

paths. An overall IFR of 0.780 suggests that the original fact still remains deducible to a significant extent. Figure 3 shows samples from these 80 active chains.

Table 3: n-step IFR for the `Harry Potter` case-study.

n	n-step chains	Active chains post edit	n-step IFR
1	1	1	0.200
2	20	14	0.814
3	30	23	0.736
4	35	30	0.484
5	14	12	0.402

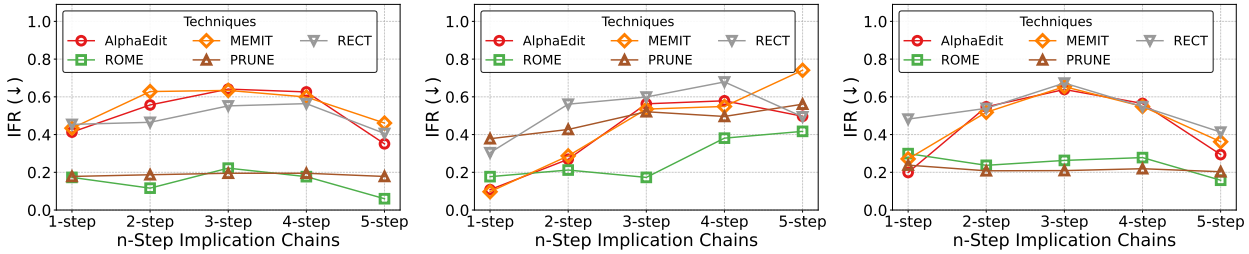
As shown in Table 3, the 1-step chain with IFR of 0.200 shows effective suppression of direct inference. However, the 2-step and 3-step chains exhibit high IFR values of 0.814 and 0.736 respectively, demonstrating high indirect fact leakage through short reasoning paths. The 4-step and 5-step chains show moderate IFR values of 0.484 and 0.402, further demonstrating persistent leakage across longer paths. Despite an Efficacy of 1.00, the original fact persists through multi-step reasoning, indicating AlphaEdit's surface-level success but failure in deeper knowledge updates. For an editing method to qualify as successful under the deep editing paradigm, the original fact must be eliminated across all reasoning paths. This case-study also highlights that traditional metrics like Efficacy are insufficient for deep editing. IFR's focus on multi-step chains provides a more robust evaluation. Further details of the case-study are in Appendix H.

6.3 Results and discussions

Table 4 presents the overall IFR, Preservation and Efficacy values for different editing techniques across GPT2-XL, Llama3-8B, and Qwen2.5-7B. For Llama3-8B, AlphaEdit achieves the highest Efficacy of 0.958, followed by PRUNE at 0.875, indicating strong performance in updating target facts. For Qwen2.5-7B, AlphaEdit achieves a perfect Efficacy of 1.000, with MEMIT also performing strongly at 0.958. For GPT2-XL, both AlphaEdit and PRUNE achieve high Efficacy scores of 1.000 and 0.917, respectively. Efficacy, however, provides limited insights into the performance of these techniques by focusing on direct edit success while neglecting the broader implications of these edits.

Table 4: Comparison of model-editing techniques for various models using IFR, Preservation (Pres.), and Efficacy (Eff.). Values are color-coded from red (lower performance) to green (higher performance).

Model	Technique	IFR (↓)						Pres. (↑)	Eff. (↑)
		Overall	1-step	2-step	3-step	4-step	5-step		
Llama3-8B	AlphaEdit	0.509	0.413	0.557	0.641	0.626	0.351	**0.890**	**0.958**
	MEMIT	0.550	0.434	0.628	0.634	0.599	0.461	0.857	0.792
	RECT	0.487	0.454	0.465	0.552	0.564	0.406	0.823	0.708
	PRUNE	0.187	0.178	0.187	0.195	0.195	0.178	0.696	0.875
	ROME	**0.134**	0.173	0.116	0.222	0.177	0.060	0.685	0.833
Qwen2.5-7B	AlphaEdit	0.496	0.108	0.269	0.563	0.579	0.497	**0.869**	**1.000**
	MEMIT	0.577	0.097	0.287	0.535	0.549	0.741	0.859	0.958
	RECT	0.569	0.304	0.561	0.599	0.679	0.494	0.851	0.750
	PRUNE	0.514	0.378	0.427	0.521	0.496	0.561	0.765	0.792
	ROME	**0.332**	0.177	0.212	0.173	0.381	0.417	0.669	0.708
GPT2-XL	AlphaEdit	0.461	0.199	0.547	0.639	0.565	0.294	0.663	**1.000**
	MEMIT	0.484	0.271	0.518	0.654	0.549	0.362	0.683	0.875
	RECT	0.516	0.482	0.539	0.673	0.548	0.413	**0.689**	0.708
	PRUNE	0.211	0.238	0.208	0.209	0.219	0.203	0.587	0.917
	ROME	**0.196**	0.299	0.237	0.263	0.278	0.158	0.500	0.792



(a) Llama3-8B (b) Qwen2.5-7B (c) GPT2-XL

Figure 4: IFR for n-step samples. A lower IFR implies lower deducibility of the supposedly-edited fact.

In contrast, IFR scores reveal significant variability across models, as shown in Fig. 4. For Llama3-8B, AlphaEdit exhibits an IFR increase from 0.413 (1-step) to 0.641 (3-step) before declining to 0.351 (5-step), indicating that the original fact remains highly deducible, particularly via mid-range chains (3-step). On Qwen2.5-7B, AlphaEdit's IFR rises steadily from 0.108 (1-step) to 0.497 (5-step), showing persistent fact leakage. For GPT2-XL, AlphaEdit's IFR increases from 0.199 (1-step) to 0.639 (3-step) before dropping to 0.294 (5-step), following a similar rise-then-fall pattern. MEMIT on Qwen2.5-7B shows a sharp IFR increase from 0.097 (1-step) to 0.741 (5-step), while on Llama3-8B, it follows a comparable rise-then-fall trend (0.434 at 1-step, 0.634 at 3-step, 0.461 at 5-step). For GPT2-XL, MEMIT's IFR rises from 0.271 (1-step) to 0.654 (3-step) before declining to 0.362 (5-step), highlighting contrasting leakage patterns. ROME and PRUNE maintain low IFR across all models, with ROME on Llama3-8B dropping to 0.060 at 5-step, and on GPT2-XL to 0.158, indicating strong reduction in original fact leakage. However, this may suggest ripple effects in related knowledge. These techniques are typically designed to edit direct facts (1-step chains), expecting their impact to diminish as chain length increases, ideally resulting in an increasing IFR curve. Most techniques on Qwen2.5-7B align with this expectation, but deviate on other models, showing a peak before declining.

The rise-then-fall IFR pattern in AlphaEdit, MEMIT, and RECT on Llama3-8B and GPT2-XL is attributed to the interplay between their editing strategies and ripple effects. As IFR relies on the product of link strengths in an implication chain, longer chains (4-5 steps) are more likely to encounter weakened links, reducing deducibility due to eroded related knowledge. These techniques disrupt broader contextual connections, causing a decline in IFR beyond mid-range chains. In contrast, ROME and PRUNE show lower IFR across all models, risking over-editing, as reflected by their Preservation scores. As illustrated in Fig. 5, ROME's Preservation is relatively low (0.685 on Llama3-8B, 0.669 on Qwen2.5-7B, 0.500 on GPT2-XL), indi-

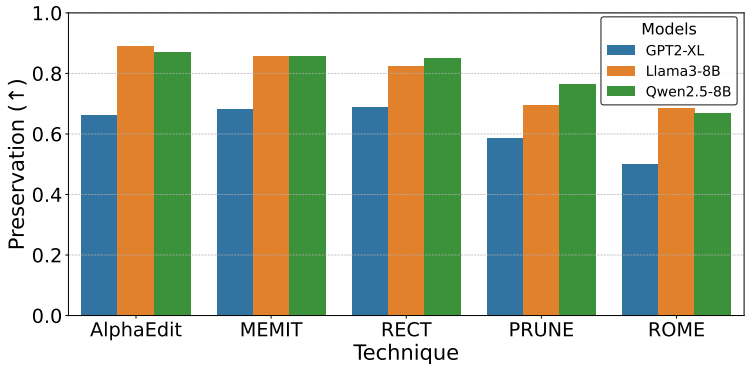
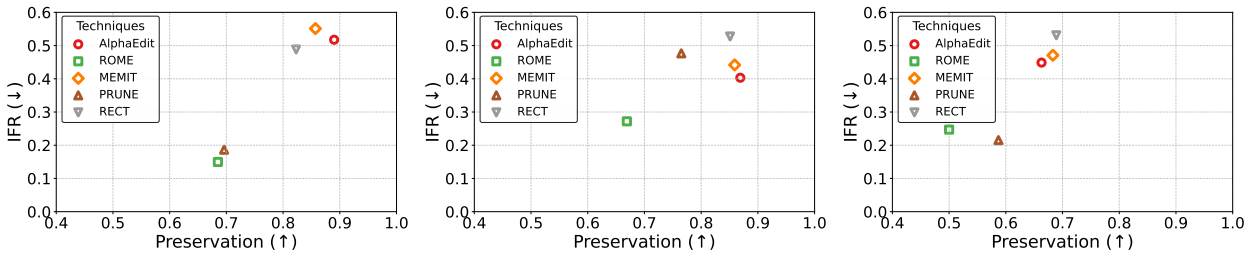


Figure 5: Preservation for different model-editing techniques. A higher Preservation indicates stronger retention of broader context integrity.



(a) Llama3-8B (b) Qwen2.5-7B (c) GPT2-XL

Figure 6: IFR vs. Preservation for different model-editing techniques, illustrating trade-offs in indirect fact recovery and related knowledge preservation.

cating poor preservation of related facts, while AlphaEdit achieves higher Preservation (0.890 on Llama3-8B, 0.869 on Qwen2.5-7B, 0.663 on GPT2-XL). GPT2-XL models show low preservation across all techniques due to high entanglement of facts stemming from its smaller size (Qin et al. (2024)). For Qwen2.5-7B, the predominantly increasing IFR curves, such as AlphaEdit's rise from 0.108 (1-step) to 0.497 (5-step), prompt additional investigations to explore its robustness over extended implication chains, detailed in Appendix A. Fig. 6 highlights the varying performance of these techniques. For users, IFR delivers critical insights into the subtle impacts of edits across implication chains, revealing strengths and weaknesses missed by existing metrics and underscoring the importance of systematic evaluation frameworks such as ThinkEval.

7 Conclusion

In this study, we discuss the challenge of maintaining consistent knowledge in LLMs under model editing. We introduced ThinkEval, a framework which offers users involved in updating and deploying a model a systematic evaluation of editing techniques. Within this framework, we defined the deep editing evaluation setting to quantify the original knowledge leakage and ripple effects caused by edits, and proposed Indirect Fact Recovery (IFR) as a metric to quantify such leakage, thus assisting these users in choosing the suitable model and the right editing technique for their use case. For evaluation, we constructed the KnowGIC benchmark, a dataset of multi-step reasoning paths. Our experiments expose significant limitations in five state-of-the-art editing techniques across three models. While these techniques effectively deal with directly queried facts, they frequently fail to eliminate indirect knowledge leakage, allowing the original information to persist. Additionally, edits often introduce unintended ripple effects that disrupt the coherence of surrounding contextual knowledge. These findings highlight the need for evaluation frameworks like ThinkEval to guide users in selecting editing methods and for the development of more holistic techniques that update knowledge reliably without compromising contextual integrity.

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A Original Model Performance on KnowGIC Queries

Qwen2.5-7B accurately answered only 81% of the queries included across all implication chains, causing inference from a significant number of chains infeasible. This may be due to the fact that Llama3-8B was utilised for fact extraction for the KnowGIC dataset. To explore this further, we conduct additional tests using Ollama (Ollama Team (2023)). These tests are run on a sample of the queries which failed to answer correctly while inferencing with the original unedited model. This is to determine whether existing queries in the dataset are not able to fetch the expected responses, or the knowledge itself is not there in the model.

Fig 7 illustrates Qwen2.5-7B's responses to three prompts designed to test its knowledge of the triplet (Hermione Granger, taught Ancient Runes by, Bathsheda Babbling). These include a direct query where the object is not present within the prompt ("Who teaches Ancient Runes to Hermione Granger?"), a query where the relationship is not present within the prompt ("What does Bathsheda Babbling teach to Hermione Granger?"), and a prompt which contains all the three elements of the triplet ("Did Bathsheda Babbling teach Hermione Granger Ancient Runes?"). The model's responses reveal significant knowledge gaps, such as denying Ancient Runes as a Hogwarts course, confusing Bathsheda Babbling with Bathilda Bagshot, and incorrectly attributing other entities. Thus, we can conclude there are gaps in Qwen2.5-7B's knowledge with respect to a few queries in KnowGIC.

Fig 8 illustrates Qwen2.5-7B's responses to three prompts designed to test its knowledge of the triplet (Nicole Richie, spouse, Joel Madden). The prompts include a direct query where the object is not present within the prompt ("Who is Nicole Richie's spouse?"), a query where the relationship is not present within the prompt ("Who is Joel Madden's spouse?"), and a prompt which contains all the three elements of the triplet ("Is Joel Madden's spouse Nicole Richie?"). The model's responses are inconsistent: it incorrectly names Blake Shelton as Nicole Richie's spouse and Ashlee Simpson as Joel Madden's spouse, despite later confirming that Joel Madden is married to Nicole Richie.

Evaluating another triplet shown in Fig 9, Don Rich was a key member of The Buckaroos and not of The Jordanaires. The Buckaroos is the backing band for Buck Owens, not Elvis Presley or Charlie Rich. Don Rich wasn't just a supporting guitarist for another act; he was the lead guitarist and a core part of the band from early 1960s until 1974. The Buckaroos were not associated with Elvis Presley or Graceland. They were Buck Owens' band, formed in Bakersfield, California. Charlie Rich, a separate artist had his own career and band, but Don Rich had no notable connection to him.

Evaluating the triplet shown in Fig 10, Lisa Marie Presley is mother of Benjamin Keough. Benjamin Keough was born on October 21, 1992, to Lisa Marie Presley and her husband Danny Keough. There's no evidence of a Benjamin Keough born to a Justin and Erin Keough. Hence, for evaluating model editing, there is a need to customize the prompts which may be specific to the model itself.

IFR trends for Qwen2.5-7B differ significantly from those of Llama3-8B, which may be due to the reason mentioned above. In Qwen2.5-7B, a higher number of implication chains remain inactive, leading to deviations from the observed trends in Llama3-8B. These errors highlight the challenges in model editing, as Qwen2.5-7B fails to accurately reflect the target triplets, underscoring the need for frameworks like ThinkEval that enable model-specific prompt customization and identification of model-specific relationships to address such deficiencies effectively.

Target Triplet: (Hermione Granger, taught Ancient Runes by, Bathsheda Babbling)

Prompt: Who teaches Ancient Runes to Hermione Granger?
Response: In the Harry Potter series, Ancient Runes is not actually a course taught at Hogwarts School of Witchcraft and Wizardry. Instead, Hermione Granger learns about ancient languages and scripts on her own. She shows an interest in Ancient Runes and spends time studying them independently.
The subject that comes closest to Ancient Runes within the wizarding curriculum at Hogwarts is Muggle Studies, which deals with the study of non-magical cultures and their inventions, including writing systems and historical texts. However, this is not directly related to Hermione's interest in ancient languages from her own studies.
In the books, Hermione's knowledge of ancient scripts such as Old Norse Runes and other similar scripts comes from her independent reading and research outside of class.

Prompt: What does Bathsheda Babbling teach to Hermione Granger?
Response: It seems there might be a mix-up in the names or titles. There is no known character named "Bathsheda Babbling" in the Harry Potter series written by J.K. Rowling, nor do they teach anyone directly.
However, I can help clarify if you meant "Bathilda Bagshot," who appears in some of the supplementary materials and books related to the Harry Potter universe. Bathilda Bagshot is a character known for her magical history books, but she doesn't specifically teach Hermione Granger anything in the main series.
If you're referring to a specific lesson or teaching that Hermione received from another character (like a professor), could you please provide more details? This would help me give you a more accurate and detailed answer.

Prompt: Did Bathsheda Babbling teach Hermione Granger Ancient Runes?
Response: No, Bathsheda Babbling did not teach Hermione Granger Ancient Runes. The character you might be thinking of is Bathilda Bagshot, who wrote "A History of Magic," a book that Hermione used to learn about Ancient Runes. However, Hermione's primary teacher for Ancient Runes was Professor Barty Crouch Jr., in his guise as Mad-Eye Moody during her third year at Hogwarts.
Hermione studied Ancient Runes alongside other subjects and delved into the subject with great interest due to its magical and historical significance. She often relied on books like "A History of Magic" for additional reading and knowledge, but her main instruction came from Professor Crouch/Moody in class.

Figure 7: Qwen2.5-7B's Responses to various prompts for the target triplet (Hermione Granger, taught Ancient Runes by, Bathsheda Babbling)

Target Triplet: (Nicole Richie, spouse, Joel Madden)

Prompt: Who is Nicole Richie's spouse?
Response: Nicole Richie's spouse is Blake Shelton. They got married on September 25, 2016. Blake Shelton is an American singer and musician, best known for being a coach on seasons 8-13 of "The Voice" and for his successful career in country music.

Prompt: Who is Joel Madden's spouse?
Response: Joel Madden, the lead singer of the band Good Charlotte and formerly of No Doubt (not to be confused with Tony Kanal who was in No Doubt), is married to Ashlee Simpson. They got married on April 15, 2006, and later had a daughter named Wilder Amour Madden. However, Joel and Ashlee/ divorced in 2019.

Prompt: Is Joel Madden's spouse Nicole Richie?
Response: Yes, Joel Madden is married to Nicole Richie. They got married on September 29, 2007, and have two children together: Jasmine Joy Madden (born in 2010) and Haven James Madden (born in 2014). Joel is the lead singer of the band Good Charlotte, while Nicole Richie is a well-known fashion designer, model, and television personality.

Figure 8: Qwen2.5-7B's Responses to various prompts for the target triplet (Nicole Richie, spouse, Joel Madden)

Target Triplet: (Don Rich, band, The Buckaroos)

Prompt: Which band was Don Rich a part of?
Response: Don Rich was a member of the country music band The Jordanaires. He joined the group in 1957 and was known for his smooth baritone vocals and his harmonies, which contributed significantly to the sound of many famous artists including Elvis Presley, Patsy Cline, and Jim Reeves. The Jordanaires are one of the most successful vocal groups in country music history, backing numerous chart-topping hits throughout their long career.

Prompt: Was Don Rich a member of The Buckaroos music band?
Response: Don Rich was indeed associated with The Buckaroos, but his role wasn't as a member of the band itself. Don Rich was a guitarist who played for the Charlie Rich Band, which supported The Buckaroos during their performances in the mid-1960s. Charlie Rich was a famous American country and rockabilly singer, and Don Rich's guitar work significantly contributed to the sound that made Charlie Rich successful. The Buckaroos were an influential band associated with Elvis Presley. They played at Presley's home studio, Graceland, and were known for their energetic performances and distinctive sound in rockabilly and country music.

Figure 9: Qwen2.5-7B's Responses to various prompts for the target triplet (Don Rich, band, The Buckaroos)

Target Triplet: (Benjamin Keough, mother, Lisa Marie Presley)

Prompt: Who is the mother of Benjamin Keough?
Response: I'm sorry, but I don't have any specific information about who the mother of Benjamin Keough might be. Without additional context or details, it's difficult to provide accurate information. The name "Benjamin Keough" does not correspond to a widely known historical figure or public personality that I can confidently identify as needing such information. If you could provide more context or specify which Benjamin Keough you're referring to (e.g., the time period, location, or any other relevant details), I might be able to assist you better.

Prompt: Is Lisa Marie Presley the mother of Benjamin Keough?
Response: Lisa Marie Presley is not the mother of Benjamin Keough. Benjamin Keough's biological parents are Justin and Erin Keough. Lisa Marie Presley passed away in 2023, and there
is no public information suggesting she has a child named Benjamin Keough. If you have more specific details or context about your question, feel free to provide it for
further clarification!

Figure 10: Qwen2.5-7B's Responses to various prompts for the target triplet (Benjamin Keough, mother, Lisa Marie Presley)

B On Human Involvement and Graph Completion

Human involvement is essential in current LLM research due to the well-known issue of hallucination. Models often produce plausible but incorrect information. Several existing knowledge editing datasets also incorporate human involvement (Deng et al. (2024); Peng et al. (2024); Tsaneva et al. (2025)). Similarly, various recent LLM studies leverage HITL feedback (John et al. (2025); Kadam (2024)) to ensure factual accuracy, address data sparsity, and improve robustness. Our method follows this standard practice to prioritize precision and interpretability.

The core objective of ThinkEval is not to obtain complete knowledge graphs but to operationalize deep editing. Because of how knowledge is ever-evolving, it is extremely difficult to empirically establish that any knowledge graph is complete. Authors in Yang et al. (2022) and Peng et al. (2023) discuss the theory of Knowledge Graph Completion. Although there are many methods for constructing knowledge graphs, it is still infeasible to create comprehensive representations of all the knowledge in a field. They further dive into the open-world problem and the incompleteness of knowledge graphs (the open-world assumption).

For the Harry Potter case-study in Section 6.2, ThinkEval generates the knowledge graph up-to 100 chains with minimal human intervention. This is not a hard limit but a design choice for our evaluation. These graphs can be expanded further using ThinkEval, making it a flexible and scalable tool for probing deep relational entanglements in LLMs.

C Comparison of Model-Editing Settings

Table 5 provides a detailed comparison between various model-editing settings. The use of specialised knowledge graphs in deep editing to infer over implication chains enables us to uncover subtle editing failures is something which other benchmarks or settings may miss. We measure whether the original facts remain deducible post-edit through reasoning paths, and also test how edits propagate through related facts. Either of the other two model-editing settings don't consider sequential reasoning to uncover "edited-out" facts.

D Counterfact Metrics for Model Editing

In evaluating model editing for LLMs, a variety of metrics assess different aspects of edit quality and impact. Based on prior work (Meng et al. (2022a)), we outline the Counterfact evaluation metrics for assessing model editing in LLMs. Existing metrics are defined for an LLM f_θ, a knowledge fact prompt (s_i, r_i), an edited target output o_i, and the model's original output o_c^i, providing a comprehensive framework to evaluate the effectiveness and robustness of edits:

Table 5: Comparison of Model-Editing Settings

Model Editing Setting	**Unstructured**	**Event-based**	**Deep Editing (Ours)**
Focus	Evaluates unstructured knowledge editing, where knowledge is represented in complex, free-form text rather than structured formats.	Edits event-driven knowledge affecting multiple facts and future tendencies; mirrors how knowledge evolves through events rather than isolated fact changes.	Evaluates deep editing to prevent fact deducibility and preserve broader context; assesses editing techniques via multi-step sequential inference.
Primary Benchmark	UnKEBench	ELKEN	KnowGIC
Dataset Creation	1,000 counterfactual unstructured texts sourced from ConflictQA.	Built on Wikidata for 1,515 event edits; GPT-3.5 paraphrasing and human verification for 6,449 factual and 10,150 tendency questions.	1,406 reasoning chains; each sample includes 1-5 multi-step questions.
Metrics Used	FactScore, MMLU, Rouge Scores, BERT Scores, BLEU	Reliability and Locality	IFR, Preservation

Efficacy. This metric quantifies the proportion of cases where the edited output o_i is more likely than the original output o_c^i when the model is queried with the prompt (s_i, r_i):

$$E_i(P_{f_\theta}[o_i|(s_i, r_i)] > P_{f_\theta}[o_c^i|(s_i, r_i)]). \tag{8}$$

Generalization. Generalization measures the proportion of cases where o_i remains more probable than o_c^i in paraphrased prompts $N((s_i, r_i))$, which rephrase the original statement while preserving its meaning:

$$E_i(P_{f_\theta}[o_i|N((s_i, r_i))] > P_{f_\theta}[o_c^i|N((s_i, r_i))]) \tag{9}$$

Specificity. Specificity evaluates the model's ability to preserve correct facts in neighborhood prompts $O((s_i, r_i))$, which are prompts about related but distinct subjects:

$$E_i(P_{f_\theta}[o_i|O((s_i, r_i))] > P_{f_\theta}[o_c^i|O((s_i, r_i))]) \tag{10}$$

Fluency. Fluency assesses the quality of the model's generated text by measuring excessive repetition through the entropy of n-gram distributions. It is computed as:

$$-\frac{2}{3}\sum_k g_2(k)\log_2 g_2(k) + \frac{4}{3}\sum_k g_3(k)\log_2 g_3(k) \tag{11}$$

where $g_n(\cdot)$ represents the frequency distribution of n-grams in the output.

Consistency. Consistency evaluates the alignment between the model's generated text and a ground-truth reference. Given a subject s, the model f_θ generates text, and the cosine similarity is computed between the TF-IDF vectors of this output and a reference Wikipedia text about the target o, ensuring factual coherence.

E Various Prompts used in ThinkEval

The ThinkEval framework employs a structured set of prompts to extract, evaluate, and edit the internal knowledge of LLMs, as illustrated in Figures 11, 12 and 13. The Fact Extraction Prompt systematically

Triplet-based Question Generation Prompt

Given a relation triplet which contains the entity, relationship and attribute, generate a question about the entity that would help elicit its relationship with the attribute. Strictly generate the output only.
Example:
Harry Potter, studied at, Hogwarts School of Witchcraft and Wizardry
Output:
Where did Harry Potter study?

Triplet: <target triplet>

Figure 11: The template of the triplet-based query generation prompt.

Chain-based Question Generation Prompt

Given a chain of alternating entities and relationships, generate a question based on all the entities and their relationships so that the answer is the last entity in the chain. Strictly generate the output only.
Example:
Harry Potter, subject, Transfiguration, taught by, Minerva McGonagall
Question:
Who teaches Transfiguration to Harry Potter?

Chain: <target chain>

Figure 12: The template of the chain-based query generation prompt.

Fact Extraction Prompt

You are a fact extraction assistant specialized in parsing Q&A data. Your task is to analyze the input and extract all fact triples (subject, relationship, object) in a precise manner from the given Question and Answer. Each triple should encapsulate a single atomic fact expressed in the text. Focus on characters, events, places. Give a list but not a numbered list.
Example:
Benedetto Varchi, profession, poet
Benedetto Varchi, work, Storia Fiorentina

Question: < question prompt>
Response: <model response>

Figure 13: The template of the fact extraction prompt.

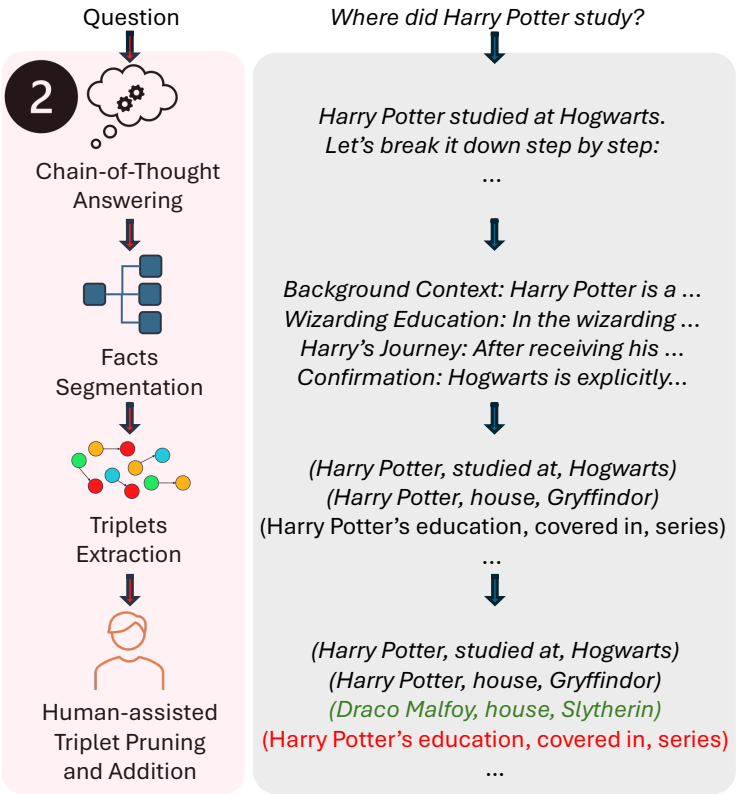

Figure 14: Automated Triplet Generation.

retrieves factual relationships from the model, enabling the construction of its internal knowledge graph by identifying entities and their connections (e.g., mapping relationships like `"Harry Potter, school, Hogwarts"`). The Triplet-Based Query Generation Prompt creates targeted queries from (subject, relation, object) triplets to evaluate factual consistency, such as `"Who teaches Ancient Runes to Hermione Granger?"` for `(Hermione Granger, taught Ancient Runes by, Bathsheda Babbling)`. Similarly, the Chain-Based Query Generation Prompt does the same for a relationship chain. By leveraging these prompts, ThinkEval effectively maps model-specific knowledge structures, identifies inconsistencies, and facilitates precise evaluation of model editing, thereby addressing deficiencies in LLMs with greater accuracy and reliability.

F Explanation of Automated Triplet Generation Process

Figure 14 illustrates the Automated Triplet Generation process, which constructs knowledge graphs by transforming a query like `"Where did Harry Potter study?"` into structured triplets. It begins with a query, followed by CoT reasoning to systematically answer it, such as covering background context, wizarding education, `Harry's` journey, and confirmation that `Hogwarts` is his school. From this, facts are extracted (e.g., `"Harry Potter studied at Hogwarts"`) and converted into triplets: `(Harry Potter, studied at, Hogwarts)`, `(Harry Potter, house, Gryffindor)`, and `(Harry Potter's education, covered in, series)`. Human-assisted pruning removes inaccuracies and irrelevant facts like `(Harry Potter's education, covered in, series)`, retaining the relevant set: `(Harry Potter, studied at, Hogwarts)`, `(Harry Potter, house, Gryffindor)`. Human-assisted triplet addition is utilised to add triplets which may be missed by the automated process even after a few iterations (such as `(Draco Malfoy, house, Slytherin)`). This process, combining CoT reasoning and human oversight, ensures accurate triplets for evaluating fact deducibility and contextual knowledge preservation.

G KnowGIC Benchmark Details

Table 6: Various base query templates, triplets, and categories in the KnowGIC benchmark.

Category	Base query templates	Sample triplet
Country of Citizenship	_____ is a citizen of	(Byron Dorgan, country of citizenship, USA)
Parental Relationship	_____'s child is	(Elvis Presley, child, Lisa Marie Presley)
Creation and Origin	_____ was created by	(Miss Piggy, created by, Jim Henson)
Marital Relationship	_____ is married to	(Victoria Beckham, spouse, David Beckham)
Sport Affiliation	_____ is associated with the sport of	(Mark Teixeira, sport, baseball)
Country of Origin	_____ was created in the country of	(basketball, country of origin, USA)
Development Origin	_____ was developed by	(Atari Jaguar, developer, Atari Corporation)
Work Location	_____ worked in the city of	(Vincent Auriol, work location, Paris)
Employers	_____ was employed by	(Ward Kimball, employer, The Walt Disney Company)
Production Entity	The company that produced _____ is	(Buick LaCrosse, produced by, General Motors)
Study Location	_____ studied at	(Harry Potter, school, Hogwarts)

To provide an overview of the KnowGIC benchmark employed in our evaluation of model-editing techniques, Table 6 presents the base queries, their corresponding triplet samples, and their respective categories. Our evaluation includes a total of 83 distinct relationship types, derived from extending these base relationships through controlled logical transformations. The dataset encompasses 1,406 samples, each being an implication chain of varying lengths (1 to 5 steps), as detailed in Table 1. Table 7 provides a few samples of the implication chains of varying lengths present in the dataset. It spans diverse knowledge domains, including country of citizenship (e.g., "What is the country of citizenship of Byron Dorgan?"), parental and marital relationships (e.g., "Who is Hillary Clinton's child?" and "Who is Nicole Richie married to?"), creation origins (e.g., "Who was Miss Piggy created by?"), sport affiliations (e.g., "Which sport is Mark Teixeira associated with?"), country of origin (e.g., "Which country was Bakersfield sound created in?"), work locations (e.g., "Which city did Petronius work in?"), production entities (e.g., "Which company is Buick LaCrosse produced by?"), and study locations (e.g., "Where did Harry Potter study?"), among others.

Each triplet represents a factual relationship that serves as the foundation for both direct queries and multi-step implication chains, which are designed to test fact deducibility and broader contextual knowledge preservation post-edit. For example, `(Harry Potter, school, Hogwarts)` is evaluated through the direct query `"Where did Harry Potter study?"` and extended into implication chains such as those exploring related entities like schoolmates and teachers. This structured representation enables a systematic evaluation of knowledge consistency across diverse domains, facilitating the evaluation of editing techniques' effectiveness in reducing deducibility (via IFR) and preserving connected knowledge (via Preservation), thus supporting the development and refinement of frameworks like ThinkEval for robust editing in LLMs. Figures 15, 16, 17, 18, 19, 20, 21 and 22 present a few of the knowledge graphs present in KnowGIC, which can be further extended using ThinkEval.

H Harry Potter Case-Study Details

Table 8 provides an overview of comparison of the existing metrics with our proposed metrics IFR, focussing on capability to evaluate indirect fact extraction. We conduct a case-study on the sample `(Harry Potter, school, Hogwarts)` from KnowGIC to evaluate the need for new metrics in deep editing, aiming to edit the fact (Hogwarts → Ilvermorny). We evaluated the edit using Efficacy and our proposed IFR metric. This

Table 7: Multi-step implication chains samples from KnowGIC. Each row presents an implication chain with the request integrated into the sample queries to evaluate fact deducibility and broader contextual integrity post-edit.

n-step	Implication chain with knowledge triplet
1	**Triplet**: *(Petronius, work location, Rome)* In which city did Petronius work?
2	**Triplet**: *(Hillary Clinton, child, Chelsea Clinton)* Who is Hillary Clinton's son-in-law? → Who is Marc Mezvinsky's wife?
3	**Triplet**: *(Ward Kimball, employer, Walt Disney)* Which character did Ward Kimball animate? → In which film does Jiminy Cricket appear? → Which company produced Pinocchio?
4	**Triplet**: *(Harry Potter, school, Hogwarts)* Who were Harry Potter's schoolmates? → Who were Ron Weasley's schoolmates? → Who taught Transfiguration to Hermione Granger? → Which school is Professor McGonagall the headmistress of?
5	**Triplet**: *(Bakersfield sound, country of origin, USA)* Which city is known for the creation of the Bakersfield sound? → In which valley is Bakersfield situated? → In which county is the San Joaquin Valley located? → In which state is Kern County situated? → What country is California located in?

Table 8: Comparison of model editing metrics. This table compares existing metrics with our proposed IFR, highlighting its focus on addressing indirect fact extraction.

Metric	What It Measures	Quantifies Indirect Fact Extraction
Efficacy	Success in outputting the edited fact for direct queries.	✗
Generalization	Performance on rephrased versions of the edited query.	✗
Specificity	Ensures unrelated queries are unaffected by the edit.	✗
Fluency	Naturalness and coherence of the model's responses post-edit.	✗
Consistency	Logical coherence across related facts.	✓ (Partially—focuses on direct consistency)
IFR	Extent to which the original fact remains deducible through multi-step reasoning.	✓
Preservation	Retention of facts related to the edited subject but not directly targeted.	✗

case-study highlights that traditional metrics like Efficacy are insufficient for deep editing tasks. IFR's focus on multi-step chains provides a more robust evaluation. These findings stress the need for advanced metrics and better editing methods for comprehensive knowledge updates in language models.

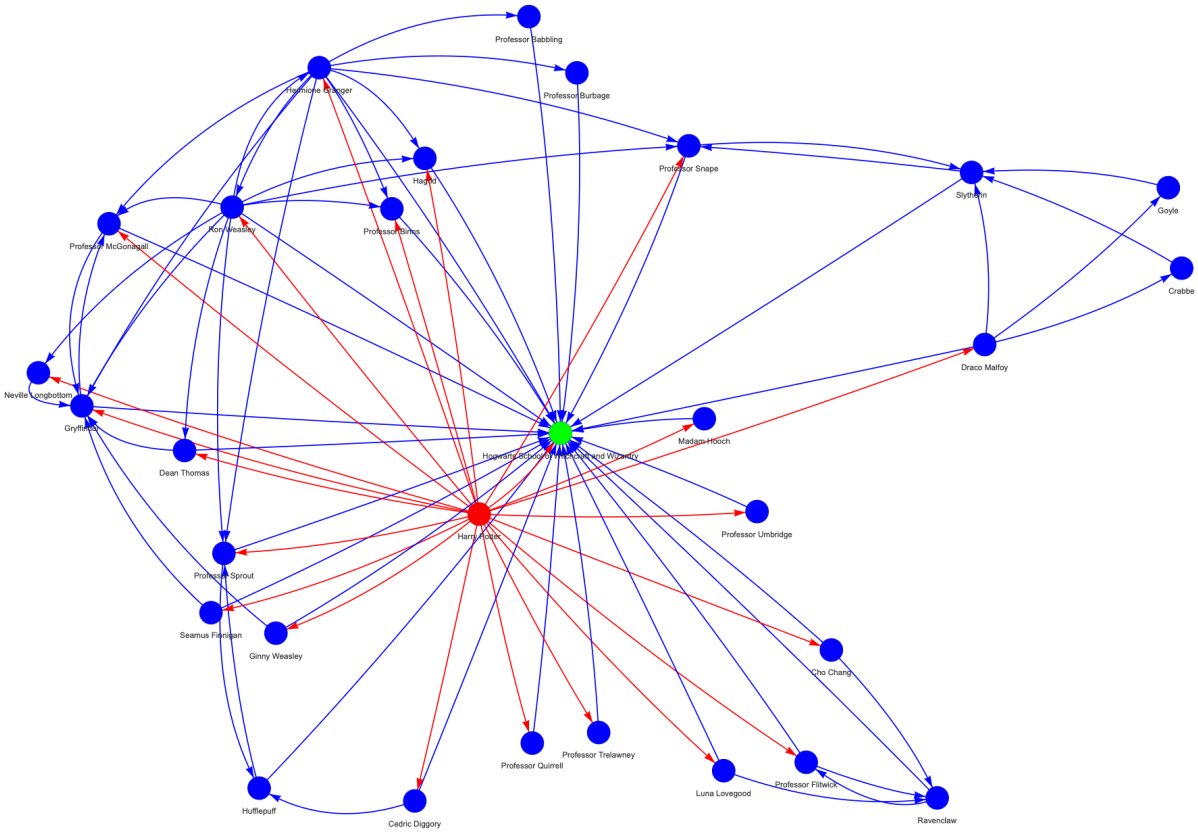

Figure 15: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Harry Potter, school, Hogwarts). The graph was expanded with the generated triplets until 100 implications paths from the initial subject to object were achieved. The red node represents the initial triplet subject, and the green node represents the initial triplet object.

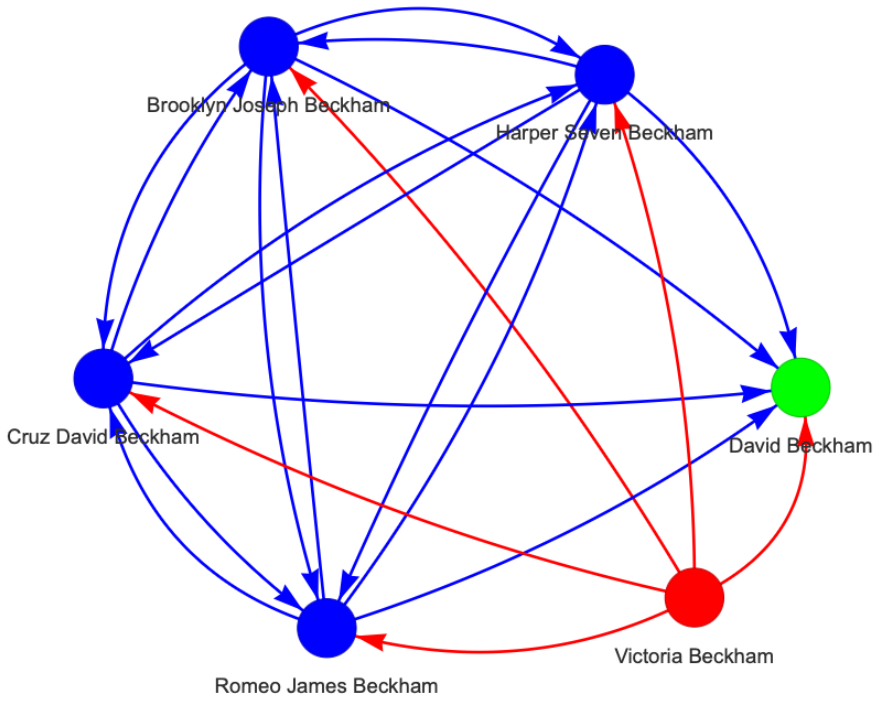

Figure 16: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Victoria Beckham, spouse, David Beckham).

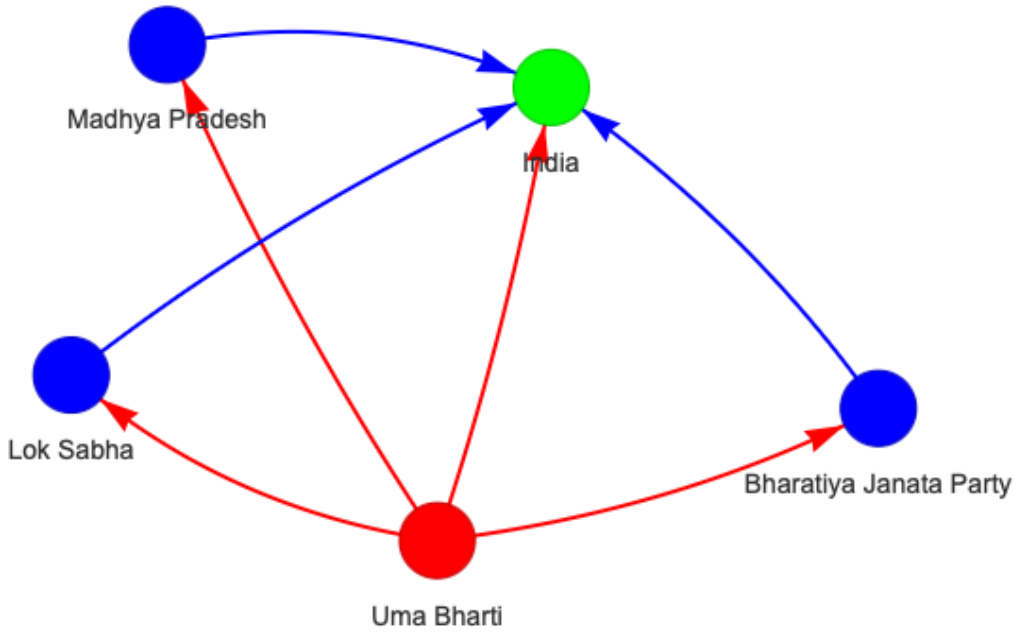

Figure 17: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Uma Bharti, country of citizenship, India).

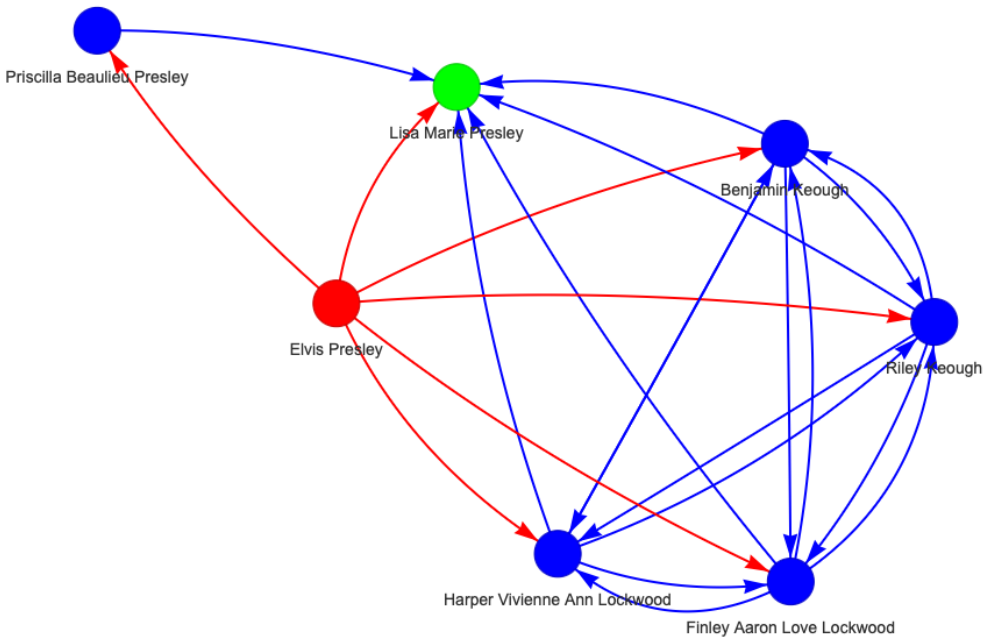

Figure 18: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Elvis Presley, child, Lisa Marie Presley).

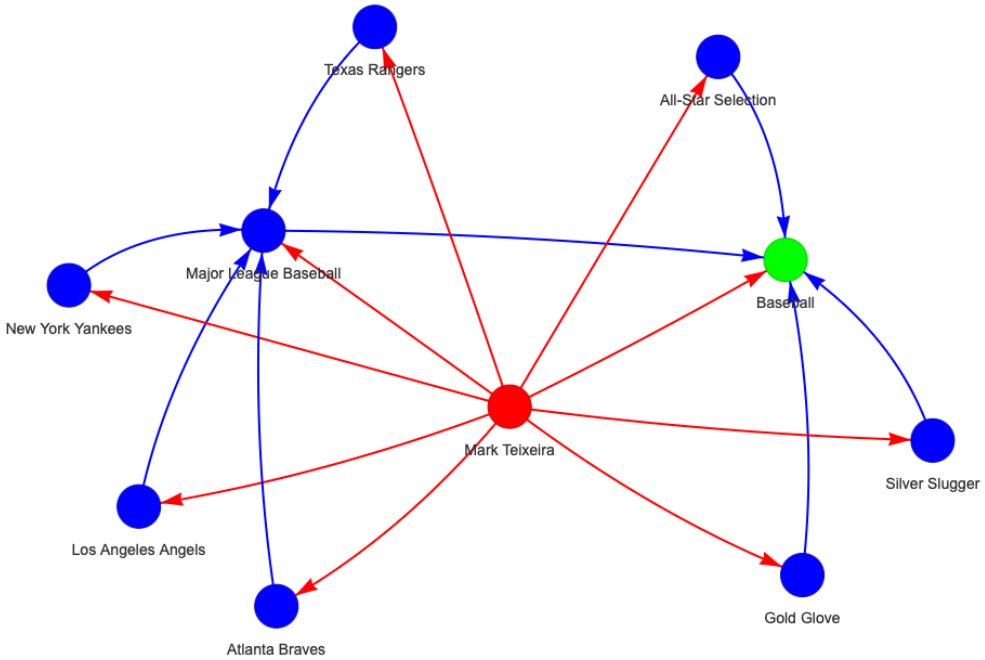

Figure 19: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Mark Teixeira, sport, baseball).

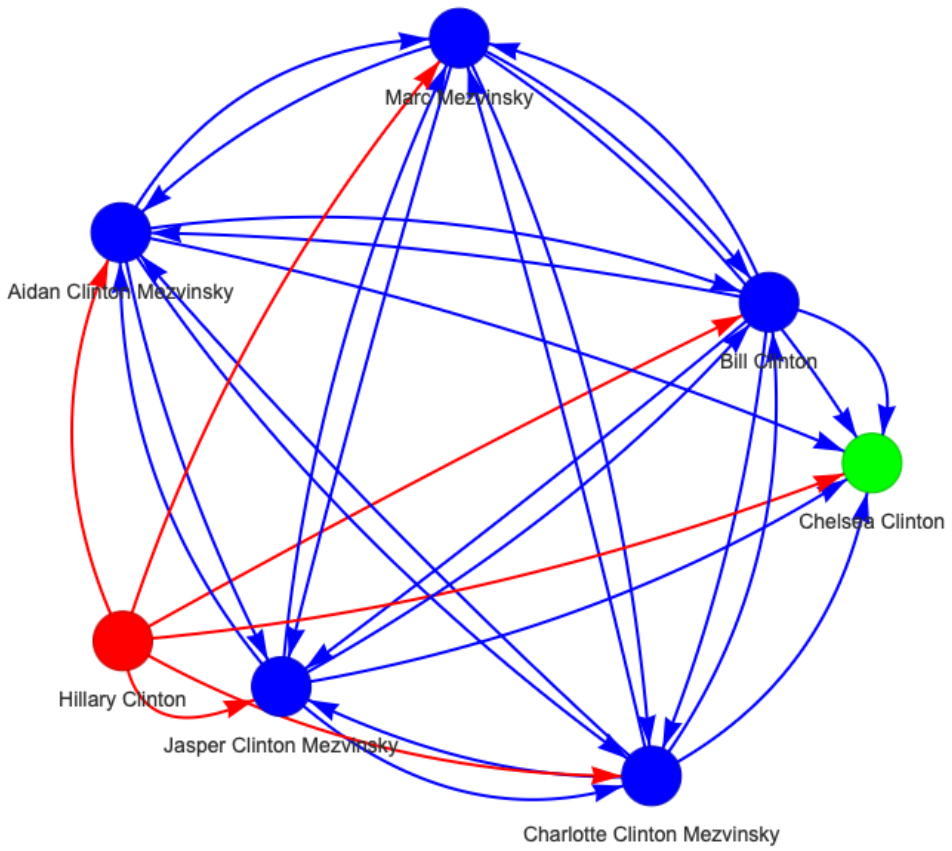

Figure 20: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Hillary Clinton, child, Chelsea Clinton).

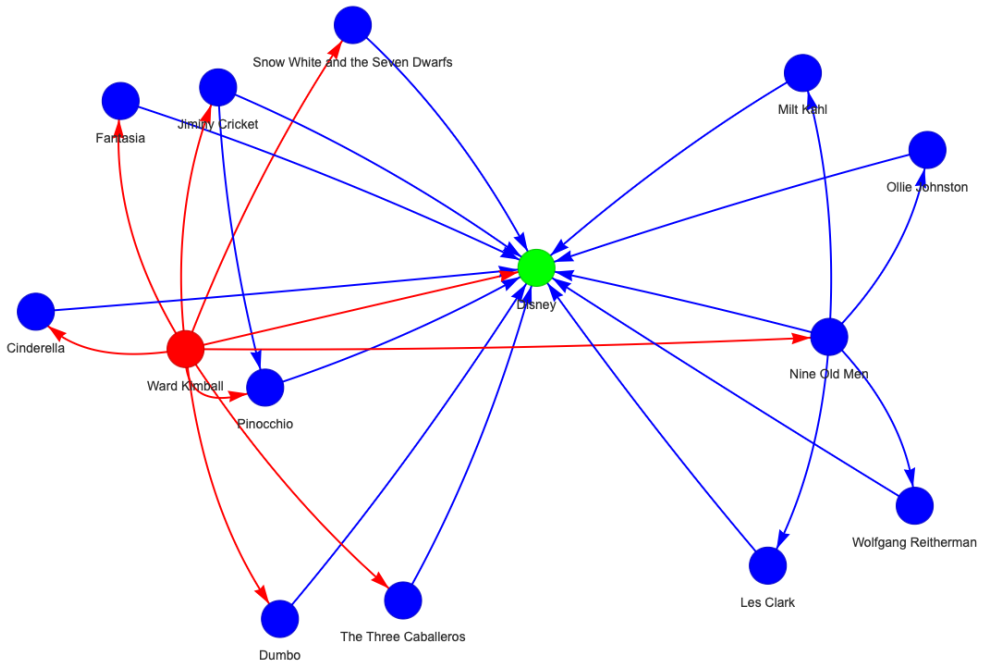

Figure 21: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Ward Kimball, employer, The Walt Disney Company).

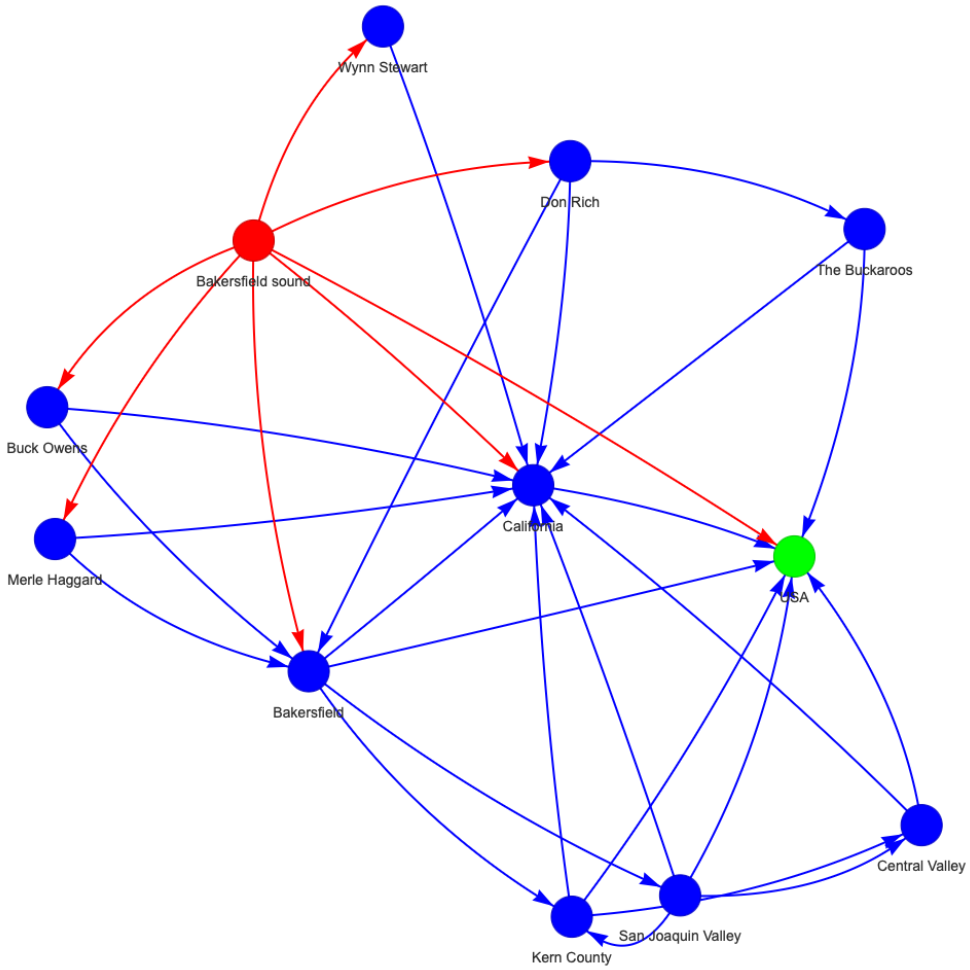

Figure 22: Sample of a constructed knowledge graph from the KnowGIC implication chains for the relationship triplet (Bakersfield sound, country of origin, USA).