

Beyond Local Edits: Embedding-Virtualized Knowledge for Broader Evaluation and Preservation of Model Editing

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Abstract

Knowledge editing methods for large language models are commonly evaluated using predefined benchmarks that assess edited facts together with a limited set of related or neighboring knowledge. While effective, such evaluations remain confined to finite, dataset-bounded samples, leaving the broader impact of editing on the model’s knowledge system insufficiently understood. To address this gap, we introduce Embedding-Virtualized Knowledge (EVK) that characterizes model knowledge through controlled perturbations in embedding space, enabling the exploration of a substantially broader and virtualized knowledge region beyond explicit data annotations. Based on EVK, we construct an embedding-level evaluation benchmark EVK-Bench that quantifies potential knowledge drift induced by editing, revealing effects that are not captured by conventional sample-based metrics. Furthermore, we propose a plug-and-play EVK-Align module that constrains embedding-level knowledge drift during editing and can be seamlessly integrated into existing editing methods. Experiments demonstrate that our approach enables more comprehensive evaluation while significantly improving knowledge preservation without sacrificing editing accuracy.

1 Introduction

Large language models (LLMs) derive their strong generalization and generation capabilities from the vast amount of knowledge acquired during pre-training (Petroni et al., 2019; Brown et al., 2020; Hoffmann et al., 2022). However, this knowledge inevitably becomes outdated or erroneous as real-world information evolves (Cao et al., 2021; Mitchell et al., 2022a), motivating the need for efficient mechanisms to update or correct specific model behaviors. While fine-tuning offers a direct solution, it typically requires modifying a large portion of model parameters, incur-

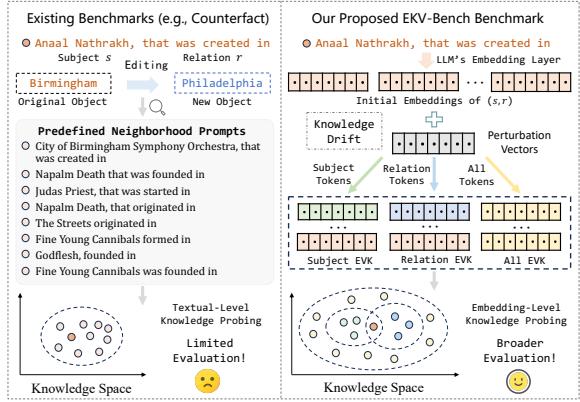


Figure 1: Comparison of conventional knowledge editing benchmarks (e.g., Counterfact) and EVK-Bench. Conventional benchmarks assess editing effects on limited textual knowledge, whereas EVK-Bench perturbs subject, relation, or full-token embeddings to construct Embedding-Virtualized Knowledge, enabling broader coverage of potentially affected knowledge in the model space.

ring high computational cost and risking catastrophic forgetting (Mitchell et al., 2022b). To address these limitations, knowledge editing has emerged as a lightweight alternative that aims to update targeted facts while minimally affecting the rest of the model (Yao et al., 2023; Gupta et al., 2024). Among existing approaches, Locate-Then-Edit (LTE) methods are particularly attractive due to their efficiency and precise parameter intervention, and have become a dominant paradigm in recent work (Meng et al., 2022; Jiang et al., 2025).

Despite rapid methodological advances, the evaluation of knowledge editing remains fundamentally constrained. As illustrated in Figure 1, existing benchmarks such as Counterfact (Meng et al., 2022) and ZsRE (Levy et al., 2017) mainly assess edited facts and a limited set of pre-defined related prompts to measure locality or specificity. Although effective at identifying side effects, such evaluations are inherently dataset-bounded: they

rely on finite, handcrafted samples and thus capture only a narrow slice of the model’s knowledge space. As a result, latent knowledge drift beyond these predefined neighborhoods is difficult to observe, and expanding evaluation coverage typically requires costly and unscalable human annotation.

To overcome these limitations, we introduce Embedding-Virtualized Knowledge (EVK) that probes model knowledge via controlled perturbations in embedding space. Instead of enumerating discrete textual prompts, EVK explores neighborhoods around factual representations, virtualizing a broader region of the knowledge space. Building on EVK, we construct EVK-Bench, an embedding-level evaluation benchmark that applies controlled perturbations of varying degrees to different factual components (e.g., subjects, relations, or entire prompts) and compares model behavior before and after editing under identical embedding-space inputs. By measuring representation consistency between edited and unedited models, EVK-Bench directly quantifies embedding-level knowledge drift induced by editing. This design enables systematic, unsupervised evaluation across varying semantic distances and can be seamlessly applied to existing datasets without additional effort.

Evaluation on EVK-Bench reveals that a range of existing LTE-style editing methods, such as RECT (Gu et al., 2024) and AlphaEdit (Fang et al., 2025b), exhibit substantially lower performance under embedding-level evaluation, despite their strong results on conventional benchmarks like Counterfact (Meng et al., 2022) and ZsRE (Levy et al., 2017). Motivated by this gap, we propose EVK-Align, a plug-and-play preservation module for LTE-type algorithms. EVK-Align leverages embedding-virtualized variations of the original edit prompt as auxiliary constraints during the editing optimization. By requiring the edited model to remain consistent with its pre-edit behavior on these virtualized inputs while still satisfying the target edit, EVK-Align constrains unintended representational drift beyond the edited fact. Extensive experiments across model architectures indicate that EVK-Align improves editing quality across both EVK-Bench and existing benchmarks. These gains are achieved without degrading downstream performance (e.g., GLUE (Wang et al., 2019)), and EVK-Align can be seamlessly integrated into LTE optimization without additional supervision or architectural changes.

In summary, our contributions are threefold:

- 1) We propose EVK-Bench, an unsupervised, embedding-level benchmark that enables broader and more scalable evaluation of knowledge editing beyond dataset-bounded samples.
- 2) We introduce EVK-Align, a plug-and-play embedding-level preservation module that improves the specificity of LTE-style knowledge editing.
- 3) We conduct extensive experiments across benchmarks, model architectures, and editing algorithms, demonstrating consistent gains in both knowledge editing and preservation.

2 Preliminaries

2.1 Memory Mechanisms in LLMs

In Transformer-based large language models (LLMs), feed-forward networks (FFNs) are commonly viewed as associative memory modules, where latent activations act as keys and the output projection matrix \mathbf{W}_{out} realizes key–value mappings that encode factual knowledge (Geva et al., 2021). Under this abstraction, structured facts such as subject–relation–object tuples are implicitly represented through key–value correspondences within FFN layers. Following prior work (Fang et al., 2025b), we treat the entire intermediate FFN activation as the key and consider the output projection matrix \mathbf{W}_{out} as the sole parameter governing key–value mappings for knowledge editing.

$$\underbrace{\mathbf{m}^l}_v = \mathbf{W}_{\text{out}}^l \underbrace{\sigma(\mathbf{W}_{\text{in}}^l \gamma(\mathbf{h}^{l-1} + \mathbf{a}^l))}_k \quad (1)$$

where \mathbf{h}^{l-1} and \mathbf{a}^l denote the input hidden state and attention output at layer l , respectively; \mathbf{W}_{in}^l and $\mathbf{W}_{\text{out}}^l$ are the FFN projection matrices; $\gamma(\cdot)$ and $\sigma(\cdot)$ denote layer normalization and the activation function. For simplicity, we denote $\mathbf{W}_{\text{out}}^l$ as \mathbf{W} in the remainder of the paper.

2.2 Model Editing under LTE Paradigm

Under the Locate-Then-Edit (LTE) paradigm, knowledge editing is formulated as a localized update to the output projection matrix \mathbf{W} of the selected FFN layer. Given an editing prompt (s, r) , the intermediate FFN activation induced by the subject token is treated as the key, and the representation associated with the desired object o defines the target value. Let (K_1, V_1) denote the key–value pair corresponding to the knowledge to be edited, and let (K_0, V_0) represent key–value

pairs associated with the model’s original knowledge. LTE-based methods (Meng et al., 2023; Fang et al., 2025c) optimize a joint objective that simultaneously enforces the new association (K_1, V_1) and preserves the original mappings (K_0, V_0) to limit interference:

$$\Delta = \arg \min_{\tilde{\Delta}} \sum_{i \in 0,1} \left| (\mathbf{W} + \tilde{\Delta}) \mathbf{K}_i - \mathbf{V}_i \right|^2 \quad (2)$$

This formulation admits a closed-form solution via the normal equations, which underlies the efficiency and numerical stability of LTE-based editing algorithms:

$$\Delta = (\mathbf{V}_1 - \mathbf{W}\mathbf{K}_1) \mathbf{K}_1^\top \left(\mathbf{K}_0\mathbf{K}_0^\top + \mathbf{K}_1\mathbf{K}_1^\top \right)^{-1} \quad (3)$$

In practice, the original key–value pairs (K_0, V_0) are approximated by aggregating FFN activations from forward passes over abundant text input reflecting the model’s pre-edit behavior (Meng et al., 2023). See Appendix B for detailed implementation steps for model editing.

3 Methodology

3.1 EVK-Bench: Embedding-Virtualized Knowledge Benchmark

Existing knowledge editing benchmarks are typically grounded in factual triples (s, r, o) and evaluate model behavior using prompts constructed from these triples and a limited set of surface-level transformations, such as paraphrasing or subject/relation replacement. While effective for pre-defined cases, such evaluations remain confined to a finite and discrete set of textual samples. To move beyond this limitation, we introduce *EVK-Bench*, an *Embedding-Virtualized Knowledge* benchmark that explores the continuous semantic neighborhood of edited knowledge directly in embedding space, enabling a more fine-grained assessment of editing specificity and impact scope.

3.1.1 Knowledge Simulation

We now describe how EVK-Bench simulates virtualized knowledge through embedding-level operations.

Initial Knowledge Representation. Given a factual triple (s, r, o), we construct an initial textual prompt P using a predefined template, which verbalizes the triple into natural language for probing the model. The prompt P is tokenized into a sequence of tokens $\{t_1, t_2, \dots, t_n\}$. Each token

t_i is mapped to its input embedding through the model’s embedding layer:

$$\mathbf{e}_i = \text{Embed}(t_i) \in \mathbb{R}^d \quad (4)$$

where d denotes the embedding dimensionality of the language model. Stacking all token embeddings yields the prompt embedding matrix:

$$\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n] \quad (5)$$

To enable targeted semantic perturbations, we identify the token spans in P that correspond to the subject s and relation r based on the prompt template and token alignment. Let \mathcal{I}_s and \mathcal{I}_r denote the index sets of tokens associated with the subject and relation, respectively. We then extract the corresponding embedding submatrices:

$$\mathbf{E}_s = \mathbf{E}[\mathcal{I}_s, :], \quad \mathbf{E}_r = \mathbf{E}[\mathcal{I}_r, :] \quad (6)$$

where $\mathbf{E}_s \in \mathbb{R}^{|\mathcal{I}_s| \times d}$ and $\mathbf{E}_r \in \mathbb{R}^{|\mathcal{I}_r| \times d}$ represent the subject-related and relation-related embedding segments.

Knowledge Drift Modeling. To systematically probe the extent to which an edit propagates beyond its intended scope, we model *knowledge drift* as controlled perturbations in embedding space. Specifically, we define drift in terms of additive embedding offsets sampled from a parameterized distribution.

Given the prompt embedding matrix $\mathbf{E} \in \mathbb{R}^{n \times d}$ and its subject and relation submatrices $\mathbf{E}_s \in \mathbb{R}^{|\mathcal{I}_s| \times d}$ and $\mathbf{E}_r \in \mathbb{R}^{|\mathcal{I}_r| \times d}$, we construct perturbation matrices by sampling from an isotropic Gaussian distribution:

$$\Delta_j \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}), \quad j \in \{s, r, a\} \quad (7)$$

where $\Delta_s \in \mathbb{R}^{|\mathcal{I}_s| \times d}$, $\Delta_r \in \mathbb{R}^{|\mathcal{I}_r| \times d}$, and $\Delta_a \in \mathbb{R}^{n \times d}$ denote the perturbation matrices applied to the subject, relation, and entire prompt embedding, respectively. The scalar σ controls the perturbation strength and determines the magnitude of semantic drift in embedding space.

Based on the target of perturbation, we define three drift types. *Subject Drift* applies perturbations only to \mathbf{E}_s , inducing localized semantic variation around the subject while preserving the original relation. *Relation Drift* perturbs \mathbf{E}_r while keeping the subject fixed, probing the robustness of relation-specific knowledge. *All Drift* applies a global perturbation to the full embedding matrix \mathbf{E} , representing a broader semantic deviation. These

drift types form expanding evaluation boundaries in the latent knowledge space.

EVK Construction. Given the perturbation matrices defined above, we construct embedding-virtualized knowledge (EVK) instances by injecting the corresponding offsets into the prompt embedding matrix. Formally, the EVK embedding matrix $\tilde{\mathbf{E}}$ is defined as:

$$\tilde{\mathbf{E}} = \begin{cases} \mathbf{E}_s + \Delta_s, & \text{Subject Drift} \\ \mathbf{E}_r + \Delta_r, & \text{Relation Drift} \\ \mathbf{E} + \Delta_a, & \text{All Drift} \end{cases} \quad (8)$$

Each resulting $\tilde{\mathbf{E}}$ defines an embedding-virtualized knowledge (EVK) instance, which represents a virtual knowledge point obtained by offsetting the original prompt embeddings in the continuous representation space. Depending on whether the offset is applied to the subject tokens, relation tokens, or all tokens, this construction yields three EVK types: Subject EVK, Relation EVK, and All EVK. For each original factual prompt, these EVK instances are generated in equal quantities and differ only at the embedding level, while the surface text remains unchanged.

By controlling the perturbation strength σ , EVK instances span semantic neighborhoods at varying distances from the original fact. EVK-Bench leverages these embedding-level variations to evaluate whether knowledge edits remain confined to the intended target or unintentionally affect nearby, semantically related knowledge. In our experiments, EVK instances are constructed from prompts in the Counterfact benchmark (Meng et al., 2022). More generally, this construction is applicable to arbitrary existing knowledge editing benchmarks (Levy et al., 2017; Rosati et al., 2024), as it operates directly at the embedding level and requires no additional human annotation, enabling an efficient and scalable way to generate evaluation instances.

3.1.2 Evaluation Metrics

EVK instances are constructed via embedding-level perturbations and do not necessarily correspond to explicit textual facts, making conventional correctness-based metrics inapplicable. Instead, we evaluate whether knowledge editing unintentionally affects semantically neighboring knowledge by measuring representation stability before and after editing. To this end, we propose two complementary metrics: *Embedding Stability* (ES) and *Text Stability* (TS).

Given an EVK instance $\tilde{\mathbf{E}}$, we feed it into the pre-edit and post-edit language models and extract the hidden states of the final output token, denoted as \mathbf{h}_{pre} and \mathbf{h}_{post} , respectively. ES is defined as their cosine similarity:

$$\text{ES} = \cos(\mathbf{h}_{\text{pre}}, \mathbf{h}_{\text{post}}) \quad (9)$$

A lower ES indicates that the edit has a larger impact on the surrounding embedding-virtualized knowledge in the latent space. While ES captures representation drift in embedding space, it is not directly observable at the textual level.

To examine whether embedding drift manifests in language behavior, we introduce a complementary text-level evaluation. We adopt attribution prompts from the Counterfact benchmark (Meng et al., 2022), which are semantically related to the original fact but lack deterministic labels, making them unsuitable for accuracy-based metrics yet well suited for stability analysis. *Text Stability* (TS) is defined as the cosine similarity between the final-token hidden states of the pre-edit and post-edit models under the same prompt. Together, embedding-level and text-level stability characterize the impact of knowledge editing on both latent representations and their induced textual behavior.

3.2 EVK-Align: Embedding-Virtualized Knowledge Alignment

EVK-Bench reveals that knowledge editing may unintentionally affect embedding-virtualized neighboring knowledge. However, existing editing methods lack explicit mechanisms to constrain such influence during optimization. To address this issue, as shown in Figure 2, we propose *EVK-Align*, a plug-and-play alignment module that regularizes the editing process by preserving model behavior on EVK instances. EVK-Align is lightweight, model-agnostic, and readily applicable to Locate-Then-Edit (LTE) style methods.

We consider a standard knowledge editing setup, where editing data $(x, y) \in D$ is considered to optimize a parameter update δ at a designated editing layer by minimizing the negative log-likelihood:

$$\mathcal{L}_{\text{Edit}} = -\frac{1}{|D|} \sum_{i=1}^{|D|} \log p_{\theta+\delta}(y | x) \quad (10)$$

As seen in Figure 2, EVK-Align augments this objective with an auxiliary alignment loss defined over embedding-virtualized knowledge. Specifically, we construct EVK instances \hat{x} by applying

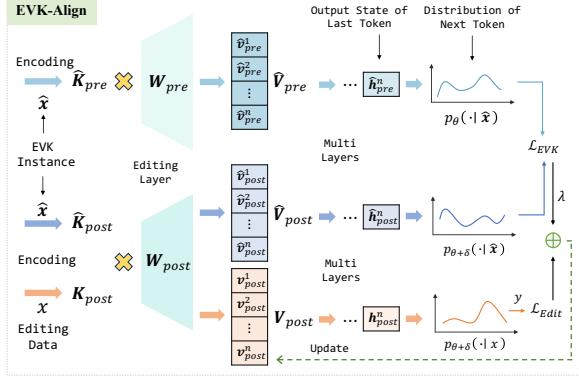


Figure 2: Computational graph of EVK-Align. EVK data is used to compute the pre-edit next-token distribution. After editing, next-token distributions are obtained for both Editing and EVK data: the Editing distribution is optimized via negative log-likelihood to enforce the edit, while the KL divergence between the pre- and post-edit EVK distributions is minimized to preserve original knowledge.

controlled perturbations to the embedding representations induced by x , following the same principle as EVK-Bench (i.e., \tilde{E} in Eq. 8). Each \hat{x} corresponds to a virtualized knowledge point in the semantic neighborhood of the edited fact.

3.2.1 Alignment Objective

For a given EVK instance \hat{x} , as shown in Figure 2, we obtain the reference output distribution $p_\theta(\cdot | \hat{x})$ from the pre-edit model, and the corresponding output distribution $p_{\theta+\delta}(\cdot | \hat{x})$ from the post-edit model. To preserve the model’s original behavior on embedding-virtualized neighboring knowledge, we minimize the Kullback–Leibler (KL) divergence between these two distributions:

$$\mathcal{L}_{EVK} = \frac{1}{N} \sum_{i=1}^N D_{KL}(p_\theta(\cdot | \hat{x}_i) \| p_{\theta+\delta}(\cdot | \hat{x}_i)) \quad (11)$$

where N denotes the number of sampled EVK instances and $D_{KL}(\cdot \| \cdot)$ denotes the KL divergence.

The overall optimization objective combines the original editing loss with the EVK alignment term:

$$\mathcal{L} = \mathcal{L}_{Edit} + \lambda \cdot \mathcal{L}_{EVK} \quad (12)$$

where λ controls the trade-off between faithful target editing and preservation of embedding-virtualized neighboring knowledge. In practice, EVK instances \hat{x} are randomly sampled from subject EVK, relation EVK, or full EVK variants to provide complementary alignment signals across different semantic perturbation patterns.

3.2.2 Progressive Regulation

Computing KL divergence over the full vocabulary is computationally expensive and may over-constrain low-probability tokens. We therefore adopt a top- k approximation for the EVK alignment loss. Given the reference distribution $p_\theta(\cdot | \hat{x}_i)$, we select the index set \mathcal{I}_k corresponding to the top- k most probable tokens:

$$\mathcal{I}_k = \text{TopK}(p_\theta(\cdot | \hat{x}_i)) \quad (13)$$

Both distributions are then renormalized over \mathcal{I}_k :

$$\begin{aligned} \tilde{p}_\theta^{(k)}(\cdot | \hat{x}_i) &= \frac{p_\theta(\cdot | \hat{x}_i)[\mathcal{I}_k]}{\sum_{j \in \mathcal{I}_k} p_\theta(j | \hat{x}_i)}, \\ \tilde{p}_{\theta+\Delta}^{(k)}(\cdot | \hat{x}_i) &= \frac{p_{\theta+\Delta}(\cdot | \hat{x}_i)[\mathcal{I}_k]}{\sum_{j \in \mathcal{I}_k} p_{\theta+\Delta}(j | \hat{x}_i)} \end{aligned} \quad (14)$$

The resulting top- k EVK alignment loss is used as an efficient approximation of \mathcal{L}_{EVK} . To enable progressive regulation of the editing process, we adopt a two-stage schedule: a smaller k is used in early iterations to impose a weak and efficient constraint that facilitates rapid convergence, while a larger k is introduced in later iterations to strengthen distributional alignment over a broader token set, thereby yielding more stable and specific edits.

4 Experiments

4.1 Experimental Setup

Datasets. We conduct experiments on two widely used knowledge editing benchmarks, ZsRE (Levy et al., 2017) and Counterfact (Meng et al., 2022), together with our proposed EVK-Bench. In our EVK-Bench, embedding-virtualized knowledge (EVK) samples are constructed by perturbing prompt embeddings initialized from CounterFact (2,000 samples in total). The drift strength is set to $\sigma = 0.3$, and for each initial embedding, we generate three additional EVK samples. Consequently, the EVK-Bench comprises a total of 6,000 embedding-based samples. For text-level evaluation on EVK-Bench, we use attribution prompts from Counterfact, resulting in a total of 5,000 textual instances.

Evaluation Metrics. We report standard knowledge editing metrics adopted by Counterfact and ZsRE, including *Efficacy* for edit success, *Generalization* for paraphrase robustness, *Specificity* to prevent over-editing, *Fluency* for generation quality, and *Consistency* for maintaining edits in longer contexts. Further details on the computation of evaluation metrics can be found in Appendix A.2.

Table 1: Performance of editing methods on GPT2-xl, LLaMA3 and GPT-J. Eff., Gen., Spe., Flu. and Consis. denote Efficacy, Generalization, Specificity, Fluency and Consistency, respectively. The best results are highlighted in bold, while the second-best results are underlined.

Method	Model	Counterfact					ZsRE			EVK-Bench (ours)	
		Eff.	Gen.	Spe.	Flu.	Consis.	Eff.	Gen.	Spe.	ES	TS
Pre-edited	GPT2-XL	20.70	23.40	78.72	626.99	31.30	24.66	24.06	24.69	100.00	100.00
ROME		52.90	51.65	52.39	569.68	4.64	52.32	46.53	20.84	54.08	56.92
MEMIT		96.30	87.25	67.61	541.76	30.22	86.79	80.32	26.32	65.26	67.92
PRUNE		93.70	84.45	53.65	493.08	20.51	53.21	50.19	21.15	59.74	61.34
RECT		95.60	86.55	67.62	547.44	30.37	88.32	81.26	25.42	67.57	69.46
AlphaEdit		99.60	95.10	70.08	607.10	40.28	97.33	90.08	25.92	67.70	<u>75.58</u>
EVK-Edit (ours)		99.80	94.05	72.31	611.33	<u>40.15</u>	98.20	91.36	25.87	69.52	76.60
Pre-edited	LLaMA3	6.70	9.95	89.98	635.49	24.35	39.48	38.32	32.02	100.00	100.00
ROME		75.10	70.60	45.20	348.06	4.19	1.47	1.56	0.24	52.08	50.56
MEMIT		94.30	90.30	70.11	617.84	30.49	92.85	90.02	<u>32.92</u>	83.67	71.40
PRUNE		82.80	80.20	56.16	591.29	28.63	37.87	35.67	23.70	74.10	64.63
RECT		94.40	90.30	70.74	618.37	<u>30.67</u>	93.25	89.96	32.83	<u>83.77</u>	72.42
AlphaEdit		98.60	91.80	77.24	625.08	32.12	93.71	90.42	32.84	83.30	<u>73.98</u>
EVK-Edit (ours)		98.80	<u>90.35</u>	80.04	629.31	30.32	94.53	90.71	<u>33.27</u>	84.43	74.74
Pre-edited	GPT-J	14.80	17.40	83.88	622.43	29.93	28.65	28.31	27.01	100.00	100.00
ROME		71.40	65.15	50.64	376.55	2.04	89.03	84.92	26.99	55.45	57.27
MEMIT		99.20	<u>95.30</u>	70.82	610.86	<u>41.73</u>	99.18	96.40	<u>27.99</u>	83.73	75.70
PRUNE		91.40	<u>90.55</u>	57.85	510.71	33.98	67.06	61.92	27.68	71.91	62.24
RECT		99.50	95.25	72.80	611.89	41.47	99.18	96.35	28.06	84.09	77.22
AlphaEdit		99.50	95.50	78.64	619.80	42.07	99.65	97.36	28.31	<u>87.13</u>	<u>83.36</u>
EVK-Edit (ours)		99.90	94.35	80.52	620.54	40.73	99.77	<u>95.95</u>	<u>28.37</u>	88.15	83.75

In addition, EVK-Bench introduces two annotation-free stability metrics: *Embedding Stability (ES)* and *Text Stability (TS)*, which quantify representation-level and text-level behavioral changes induced by editing, respectively, and serve as complementary indicators of editing specificity.

Base Models and Baselines. Experiments are conducted on three representative language models commonly used in knowledge editing studies: GPT2-XL (1.5B) (Radford et al., 2019), GPT-J (6B) (Wang and Komatsuzaki, 2021), and LLaMA3-8B (Team, 2024). As this work focuses on LTE paradigms, and our EVK-Align is also designed for this setting, we compare against established LTE methods, including ROME (Meng et al., 2022), MEMIT (Meng et al., 2023), PRUNE (Ma et al., 2025), RECT (Gu et al., 2024), and AlphaEdit (Fang et al., 2025b). Our main method EVK-Edit is built on top of AlphaEdit by incorporating the EVK-Align constraint, and in our analysis (Section 4.3) we also evaluate the effect of adding EVK-Align to other editing methods to demonstrate its general applicability.

Implementation Details. For EVK-Edit, the hyperparameters are set as follows: $\sigma = 0.1$, $\lambda = 0.3$, $N = 1$ for GPT2-XL; $\sigma = 0.2$, $\lambda = 0.05$, $N = 1$

for LLaMA3; and $\sigma = 0.1$, $\lambda = 0.3$, $N = 1$ for GPT-J. All models follow the same progressive top- k schedule with $k = 10$ in early stages and $k = 50$ later. Experiments are conducted over 1,000 editing rounds using a single NVIDIA A800 (80GB) GPU. ROME edits one sample per round, while other methods perform batch editing with 100 samples per round.

4.2 Main Results

As summarized in Table 1, we conducted a comprehensive performance comparison between EVK-Edit and other Locate-Then-Edit algorithms on the Counterfact, ZsRE, and our EVK-Bench benchmarks.

Existing knowledge editing methods perform well on conventional benchmarks but show clear limitations on EVK-Bench. As summarized in Table 1, strong baselines such as AlphaEdit, MEMIT, and RECT achieve high Efficacy scores on Counterfact and ZsRE, often exceeding 90, indicating effective editing on standard factual benchmarks. However, their performance drops noticeably on EVK-Bench, with ES and TS scores falling below 90 and in some cases below 60. For example, on GPT2-XL, AlphaEdit achieves 99.6 Efficacy

on Counterfact and 97.33 on ZsRE, but its EVK-Bench scores are only 67.70 (ES) and 75.58 (TS). Similar trends on LLaMA3 and GPT-J indicate that conventional benchmarks may overestimate the robustness and generalization of existing editing methods.

EVK-Edit matches or surpasses baseline performance on standard benchmarks with a controlled trade-off. Across all three model families, EVK-Edit achieves comparable or slightly higher Efficacy than strong baselines while consistently improving Specificity. On LLaMA3, for instance, EVK-Edit increases Specificity on Counterfact from 77.24 (AlphaEdit) to 80.04 and achieves the highest Specificity on ZsRE. GPT2-XL and GPT-J show similar patterns, attaining top or near-top Specificity while preserving high Efficacy. We observe slight reductions in Consistency on Counterfact relative to AlphaEdit, reflecting a controlled trade-off: edits are more localized, which reduces interference with non-target knowledge but may constrain long-context alignment.

EVK-Edit demonstrates clear advantages on EVK-Bench, preserving broader embedding-level knowledge. On EVK-Bench, EVK-Edit consistently achieves the highest ES and TS scores across GPT2-XL, LLaMA3, and GPT-J, confirming stronger embedding-level and text-level stability under EVK perturbations. For example, on GPT-J, ES increases from 87.13 (AlphaEdit) to 88.15 and TS reaches 83.75, with comparable gains on the other models. These results validate that the embedding-virtualized knowledge preservation mechanism effectively constrains edits to the target knowledge while reducing unintended propagation to neighboring latent knowledge, demonstrating that EVK-Edit extends improvements beyond conventional factual benchmarks into the model’s latent knowledge space.

4.3 Analysis

As a *plug-and-play* module, EVK-Align can be integrated into various LTE algorithms, improving knowledge editing specificity with minimal impact on overall efficacy. In this section, we provide a more detailed analysis of its effects.

4.3.1 General Language Ability Evaluation

To assess potential impacts on general language capabilities, we evaluate LTE-based models augmented with EVK-Align on six GLUE tasks: SST (Socher et al., 2013), MRPC (Dolan and Brockett,

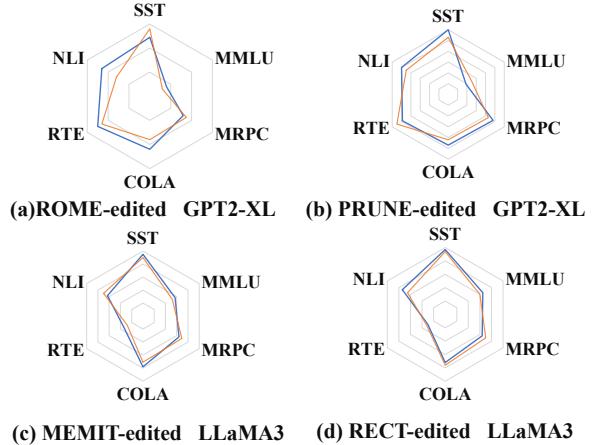


Figure 3: Performance of different LTE editing algorithms on the GLUE benchmark. Blue lines represent models enhanced with EVK-Align, and orange lines correspond to the baseline algorithms, with a total of 1000 edits performed.

2005), MMLU (Hendrycks et al., 2021), RTE (Bentivogli et al., 2009), CoLA (Warstadt et al., 2019), and NLI (Williams et al., 2018). As shown in Figure 3, performance remains generally stable, with modest gains on several benchmarks and minor declines on a few tasks. These results indicate that EVK-Align mainly improves editing specificity with minimal impact on general language understanding, making it suitable for integration into LTE pipelines without degrading overall linguistic competence.

4.3.2 Improvement with EVK-Align Module

We further evaluate EVK-Align on standard knowledge editing benchmarks, including Counterfact and ZsRE. As shown in Figure 4, EVK-Align yields consistent performance improvements across a range of LTE-based editing algorithms. Methods with moderate baseline performance, such as ROME and PRUNE, benefit the most—ROME, in particular, achieves nearly a 10-point gain in Efficacy. In contrast, strong baselines like MEMIT and RECT exhibit more modest improvements, indicating diminishing returns as baseline performance increases. Overall, these results suggest that EVK-Align effectively enhances editing specificity and stabilizes knowledge updates, providing substantial gains for moderately performing methods while still offering incremental benefits for state-of-the-art approaches.

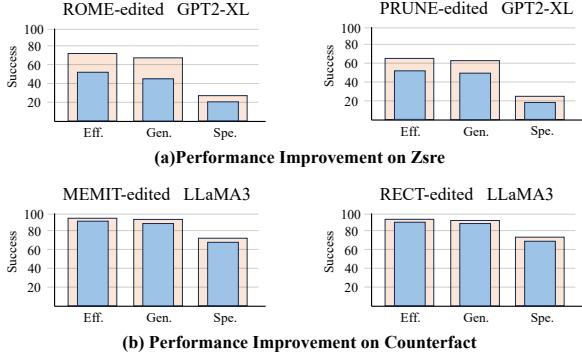


Figure 4: Performance of different LTE editing algorithms on the ZsRE and Counterfact benchmarks. The pink bars represent models augmented with EVK-Align, and the blue bars denote the baseline editing algorithms, with a total of 1000 edits performed.

4.3.3 Hyperparameter Analysis

In practical applications, the performance of EVK-Align is sensitive to hyperparameter settings, and optimal values may vary across different models and editing algorithms. For our study on LLaMA-3, we focus on four key hyperparameters of EVK-Edit. To ensure controlled comparison, we adopt the following baseline configuration: $\sigma = 0.3$, $\lambda = 0.1$, $N = 1$, and $\text{top-}k = 10$ for both stages, unless otherwise specified. Each hyperparameter is varied independently to observe effects on Efficacy (Eff.), Generalization (Gen.), Specificity (Spe.), and runtime. As shown in Table 2, we can draw the following observations:

Knowledge drift strength σ : Reducing σ from 0.5 to 0.1 increases Specificity (Spe.) from 77.65 to 80.32, indicating that the model better preserves semantically related neighboring knowledge, while slightly decreasing Generalization (Gen.) from 90.90 to 90.15, reflecting a minor reduction in propagation of edits to paraphrased prompts.

Alignment strength λ : Increasing λ from 0.1 to 1.0 substantially improves Specificity (Spe.) from 78.34 to 80.47. However, higher λ also leads to noticeable drops in both Efficacy (Eff.) and Generalization (Gen.), suggesting that overly aggressive alignment may constrain edits excessively and reduce overall editing effectiveness.

Number of reference EVK samples N : Raising N from 1 to 10 provides marginal gains in Generalization and Specificity, mitigating some side effects of EVK-Align. However, runtime increases almost linearly with N (from 5.85s to 20.51s), indicating a trade-off between robustness and efficiency.

Second-stage top- k in KL divergence: Variations

Table 2: Hyperparameter analysis for our EVK-Edit method on the Counterfact benchmark.

σ	λ	N	k	Eff.	Gen.	Spe.	Time
<i>Knowledge Drift Strength σ</i>							
0.3	0.1	1	10	99.30	90.40	78.34	5.85s
0.1	0.1	1	10	98.60	90.15	80.32	6.34s
0.5	0.1	1	10	99.10	90.90	77.65	5.62s
<i>Alignment Strength λ</i>							
0.3	0.1	1	10	99.30	90.40	78.34	5.85s
0.3	0.5	1	10	98.70	89.75	79.86	6.42s
0.3	1.0	1	10	98.10	89.35	80.47	6.73s
<i>Number of Reference EVK samples N</i>							
0.3	0.1	1	10	99.30	90.40	78.34	5.85s
0.3	0.1	5	10	99.20	90.65	78.68	12.72s
0.3	0.1	10	10	99.20	90.70	78.17	20.51s
<i>Second-stage Top-k in KL Divergence</i>							
0.3	0.1	1	10	99.30	90.40	78.34	5.85s
0.3	0.1	1	20	98.90	90.35	78.53	5.97s
0.3	0.1	1	50	99.20	90.55	78.66	6.53s

in top- k have limited impact on Efficacy and Generalization. While larger k values may slightly improve Specificity (from 78.34 to 78.66), they also increase computational overhead, suggesting that overly large k is unnecessary in practice.

Overall, this analysis provides practical guidelines for configuring EVK-Edit hyperparameters: σ and λ primarily control the locality and intensity of edits, N balances robustness and runtime, and top- k offers fine-grained tuning with minimal effect on performance.

4.3.4 Knowledge Space Analysis

Previous analyses have indicated that EVK-Bench provides a broader evaluation of editing algorithm specificity compared to traditional pre-defined neighborhood prompts such as CounterFact. Hence, we conduct 2,010 rounds of editing and present the visualization of initial prompts, predefined neighborhood prompts, and EVK-Bench within the 2D knowledge space, employing UMAP (McInnes and Healy, 2018) for dimensionality reduction.

As shown in the Figure 5, EVK-Bench provides a complementary assessment of editing algorithm specificity, as its embeddings occupy distinct regions in the feature space compared to those of

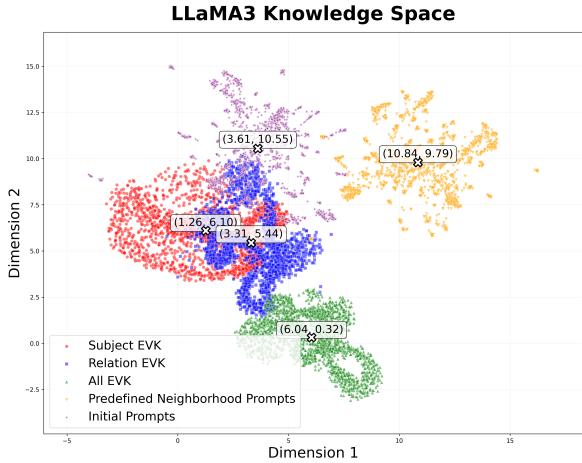


Figure 5: Embedding distributions of initial editing points, predefined related knowledge (i.e., neighborhood prompts in Counterfact), and EVK instances after dimensionality reduction, showing that EVK-Bench covers a broader knowledge space.

predefined neighborhood prompts. Notably, under the LLaMA3 model, EVK-Bench embeddings are distributed around the initial prompts, leading to a more stringent and reliable specificity evaluation. This demonstrates that EVK-Bench explores a broader region of the knowledge space, offering valuable insights and directions for specificity assessment in the field of model editing.

5 Related Work

Parameter-Modifying Model Editing. Parameter-modifying knowledge editing methods directly update model weights to modify factual knowledge. A dominant paradigm is Locate-Then-Edit, which identifies knowledge-bearing components and applies localized updates to feed-forward layers, as in ROME (Meng et al., 2022), MEMIT (Meng et al., 2023), PRUNE (Ma et al., 2025), RECT (Gu et al., 2024), and AlphaEdit (Fang et al., 2025b). Another line employs meta-learned editors to directly predict parameter updates, often in a single forward pass, such as KE (Cao et al., 2021), MEND (Mitchell et al., 2022a), and InstructEdit (Zhang et al., 2024). EVK-Align introduces an explicit alignment constraint that regulates how parameter updates affect neighboring representations, enabling more localized and controlled edits within existing frameworks.

Parameter-Preserving Model Editing. This class of approaches avoid modifying the base model by storing updated knowledge in external modules or auxiliary structures. Representative

methods include memory- or module-based designs such as SERAC (Mitchell et al., 2022b), GRACE (Hartvigsen et al., 2023), MELO (Yu et al., 2024), and T-Patcher (Huang et al., 2023), as well as prompt-based techniques like Mem-Prompt (Madaan et al., 2022) and IKE (Zheng et al., 2023). More recent work, such as WISE (Wang et al., 2024), further advances this line by introducing structured memory designs to balance reliability and generalization. While these methods enable reversible editing, evaluation relies on discrete prompts. Our architecture-agnostic EVK-Bench assesses latent effects across both parameter-modifying and parameter-preserving approaches.

Evaluation of Knowledge Editing. Existing benchmarks primarily evaluate knowledge editing using discrete textual prompts. Counterfact (Meng et al., 2022) and ZsRE (Levy et al., 2017) assess edit efficacy, generalization, and locality, while recent datasets extend evaluation to long-form generation (Rosati et al., 2024), multi-hop reasoning (Zhong et al., 2023), multilingual settings (Fang et al., 2025a), and multimodal knowledge (Du et al., 2025). However, these benchmarks rely on discrete prompts and provide limited insight into latent knowledge changes beyond predefined prompts. EVK-Bench addresses this gap by probing the continuous embedding neighborhood of edited knowledge, enabling annotation-free evaluation of representation stability and its textual effects, and guiding the design of controlled editing constraints such as EVK-Align.

6 Conclusion

This paper presents EVK-Bench, an embedding-based, annotation-free evaluation framework for systematically analyzing knowledge editing side effects across controlled semantic neighborhoods. By introducing Embedding Stability (ES) and Text Stability (TS) metrics, EVK-Bench reveals representation and behavioral drift that is invisible to conventional prompt-level benchmarks. Guided by this perspective, we further propose EVK-Align, a plug-and-play alignment mechanism that explicitly constrains edit propagation in embedding-virtualized knowledge space. Integrated into existing editing pipelines, EVK-Align consistently improves editing specificity while preserving efficacy and generation quality, offering a practical and principled approach to more controllable model editing.

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A Experimental Details

A.1 Datasets

Our experiments employ two established benchmarks for evaluating model editing techniques:

- **CounterFact** (Meng et al., 2022) is a dataset designed to assess the robustness of factual editing by contrasting counterfactual assertions with factual statements. A key challenge in this benchmark stems from the initial lower likelihood assigned to counterfactual claims. It constructs out-of-distribution samples by substituting the subject entity with semantically similar entities while keeping the predicate unchanged. Similar to ZsRE, CounterFact provides metrics for evaluating editing efficacy, generalization, and specificity. Additionally, it includes multiple paraphrased prompts to assess the textual quality of model outputs, with a particular focus on fluency and semantic consistency.
- **ZsRE** (Levy et al., 2017) is a question-answering dataset that employs questions generated through back-translation as semantically equivalent variants. Following established conventions, natural language questions serve as out-of-scope samples for evaluating editing locality. Each instance in ZsRE comprises a subject string and target answers for assessing editing success, alongside rephrased questions for generalization evaluation and unrelated questions for specificity assessment.

A.2 Evaluation Metrics

We adopt standard evaluation protocols for both datasets, defined as follows:

A.2.1 Metrics for ZsRE

Given a language model f_θ , a factual prompt (s_i, r_i) , an editing target o_i , and the model’s original output o_i^c :

- **Efficacy** quantifies the success rate of factual editing, computed as the average top-1 accuracy on the edited samples:

$$\text{Efficacy} = \frac{1}{N} \sum_{i=1}^N \mathbb{I} \left[o_i = \arg \max_o P_{f_\theta}(o | (s_i, r_i)) \right] \quad (15)$$

- **Generalization** measures the model’s performance on semantically equivalent prompts $N((s_i, r_i))$, evaluated via average top-1 accuracy:

$$\text{Generalization} = \frac{1}{N} \sum_{i=1}^N \mathbb{I} \left[o_i = \arg \max_o P_{f_\theta}(o | N((s_i, r_i))) \right] \quad (16)$$

- **Specificity** ensures that edits do not propagate to unrelated samples $O((s_i, r_i))$, assessed by the preservation of original predictions:

$$\text{Specificity} = \frac{1}{N} \sum_{i=1}^N \mathbb{I} \left[o_i^c = \arg \max_o P_{f_\theta}(o | O((s_i, r_i))) \right] \quad (17)$$

A.2.2 Metrics for CounterFact

Given the same notation as above:

- **Efficacy** measures the proportion of cases where the edited target o_i achieves higher probability than the original o_i^c :

$$\text{Efficacy} = \frac{1}{N} \sum_{i=1}^N \mathbb{I} [P_{f_\theta}(o_i | (s_i, r_i)) > P_{f_\theta}(o_i^c | (s_i, r_i))] \quad (18)$$

- **Generalization** evaluates performance on paraphrased prompts $N((s_i, r_i))$:

$$\text{Generalization} = \frac{1}{N} \sum_{i=1}^N \mathbb{I}[P_{f_\theta}(o_i | N((s_i, r_i))) > P_{f_\theta}(o_i^c | N((s_i, r_i)))] \quad (19)$$

- **Specificity** assesses preservation on neighborhood prompts $O((s_i, r_i))$ about related subjects:

$$\text{Specificity} = \frac{1}{N} \sum_{i=1}^N \mathbb{I}[P_{f_\theta}(o_i | O((s_i, r_i))) > P_{f_\theta}(o_i^c | O((s_i, r_i)))] \quad (20)$$

- **Fluency** quantifies the naturalness of generated text using n-gram distribution entropy:

$$\text{Fluency} = -\frac{2}{3} \sum_k g_2(k) \log_2 g_2(k) + \frac{4}{3} \sum_k g_3(k) \log_2 g_3(k) \quad (21)$$

where $g_n(\cdot)$ denotes the n -gram frequency distribution.

- **Consistency** measures semantic alignment between model-generated text and reference Wikipedia content using cosine similarity of TF-IDF vectors:

$$\text{Consistency} = \cos(\text{TF-IDF}(f_\theta(s)), \text{TF-IDF}(\text{Ref}(o))) \quad (22)$$

A.3 Baseline Methods

We compare against four representative model editing approaches:

- **ROME** (Meng et al., 2022) identifies and modifies key neuron activations in intermediate feed-forward layers to update specific factual associations. This method demonstrates that mid-layer modules serve as crucial repositories for factual knowledge, enabling precise model manipulation through targeted weight adjustments.
- **MEMIT** (Meng et al., 2023) extends ROME’s approach with a scalable multi-layer update algorithm for efficiently inserting numerous factual memories into transformer models. By targeting causal mediator weights across transformer modules, MEMIT supports batch editing of thousands of associations while maintaining model coherence.
- **PRUNE** (Ma et al., 2025) incorporates condition number constraints during sequential editing to preserve general model capabilities. By bounding perturbations to stored knowledge through numerical regularization, PRUNE mitigates performance degradation as the number of edits increases.
- **RECT** (Gu et al., 2024) addresses unintended side effects on general abilities through regularization of weight updates. This approach prevents excessive alterations that lead to overfitting, thereby maintaining both editing performance and broader task capabilities.
- **AlphaEdit** (Fang et al., 2025b) mitigates overfitting and capability degradation in large language models during sequential editing through null-space constrained projection, which balances knowledge update with preservation. This method projects parameter perturbations onto the null space of the original knowledge matrix, minimizing their impact on both retained knowledge and the model’s general abilities. Consequently, AlphaEdit enables efficient knowledge editing while maintaining the model’s original performance across diverse tasks such as natural language understanding and generation.

B Implementation Details of Current Model Editing

B.1 Model Editing Framework

Model editing seeks to adapt pre-trained language models by modifying specific factual associations, typically transforming an original knowledge triple (s, r, o) into an updated version (s, r, o^*) . The objective is for the edited model to accurately recall the new information o^* when prompted with natural language queries like “Who is the President of the United States?” (Meng et al., 2022).

Recent advancements in *locating-and-editing* methodologies have established a systematic framework for effective model modification. These approaches generally follow a three-stage process:

B.1.1 Stage 1: Identifying Causal Layers

The initial phase determines which feed-forward network (FFN) layers are most influential for the target knowledge. This is achieved through causal analysis techniques (Meng et al., 2022), where Gaussian noise is injected into hidden representations at various layers. By progressively restoring these representations to their original values and observing recovery in model predictions, the specific layers most responsible for the factual association can be identified as editing targets.

B.1.2 Stage 2: Computing Target Representations

The second stage derives the desired output representations for the identified layers. According to the key-value memory interpretation of transformer FFNs, the key vector k , encoding the subject-relation pair (s, r) , is transformed through output weights W_l^{out} to produce the value vector v representing the original object o :

$$k \triangleq \sigma(W_l^{in} \gamma(h^{l-1} + a^l)), \quad v \triangleq m_l = W_l^{out} k. \quad (23)$$

For knowledge editing, v must be replaced with a new vector v^* encoding o^* . This is typically formulated as an optimization problem:

$$v^* = v + \arg \min_{\delta_l} \left(-\log P_{f_{W_l^{out}}(m_l + \delta_l)}[o^* | (s, r)] \right), \quad (24)$$

where $f_{W_l^{out}}(m_l + \delta_l)$ denotes the model with modified intermediate activations, optimized to maximize the likelihood of the target output o^* .

B.1.3 Stage 3: Updating Model Parameters

The final stage modifies the weight matrix W_l^{out} to accommodate the new knowledge while preserving existing associations. Defining two sets of key-value pairs:

$$\mathcal{K}_0 = [k_1 | k_2 | \cdots | k_n], \quad \mathcal{V}_0 = [v_1 | v_2 | \cdots | v_n], \quad (25)$$

$$\mathcal{K}_1 = [k_{n+1} | k_{n+2} | \cdots | k_{n+u}], \quad \mathcal{V}_1 = [v_{n+1}^* | v_{n+2}^* | \cdots | v_{n+u}^*], \quad (26)$$

where $\mathcal{K}_0, \mathcal{V}_0$ represent n original associations and $\mathcal{K}_1, \mathcal{V}_1$ represent u new associations.

The optimization objective becomes:

$$\tilde{W}_l^{out} \triangleq \arg \min_{\hat{W}} \left(\sum_{i=1}^n \|\hat{W}k_i - v_i\|^2 + \sum_{i=n+1}^{n+u} \|\hat{W}k_i - v_i^*\|^2 \right). \quad (27)$$

This constrained least-squares problem admits a closed-form solution through the normal equations:

$$\tilde{W}_l^{out} = (\mathcal{K}\mathcal{K}^\top)^{-1}\mathcal{K}\mathcal{V}^\top, \quad (28)$$

where $\mathcal{K} = [\mathcal{K}_0 | \mathcal{K}_1]$ and $\mathcal{V} = [\mathcal{V}_0 | \mathcal{V}_1]$. This formulation ensures minimal perturbation to the original model while effectively incorporating the edited knowledge.