

# UnKE: Unstructured Knowledge Editing in Large Language Models

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## Abstract

Recent knowledge editing methods have primarily focused on modifying structured knowledge in large language models, heavily relying on the assumption that structured knowledge is stored as key-value pairs locally in MLP layers or specific neurons. However, this task setting overlooks the fact that a significant portion of real-world knowledge is stored in an unstructured format, characterized by long-form content, noise, and a complex yet comprehensive nature. The "knowledge locating" and "term-driven optimization" techniques conducted from the assumption used in previous methods (e.g., MEMIT) are ill-suited for unstructured knowledge. To address these challenges, we propose a novel unstructured knowledge editing method, namely UnKE, which extends previous assumptions in the layer dimension and token dimension. Firstly, in the layer dimension, we discard the "knowledge locating" step and treat first few layers as the key, which expand knowledge storage through layers to break the "knowledge stored locally" assumption. Next, we replace "term-driven optimization" with "cause-driven optimization" across all inputted tokens in the token dimension, directly optimizing the last layer of the key generator to perform editing to generate the required key vectors. By utilizing key-value pairs at the layer level, UnKE effectively represents and edits complex and comprehensive unstructured knowledge, leveraging the potential of both the MLP and attention layers. Results on newly proposed unstructured knowledge editing dataset (UnKEBench) and traditional structured datasets demonstrate that UnKE achieves remarkable performance, surpassing strong baselines.

## 1 Introduction

Ensuring the accuracy and currency (Xu et al., 2023) of the knowledge stored within the intrinsic parameters of large language models (LLMs) has

become increasingly critical with their widespread deployment. Knowledge editing (Yao et al., 2023) emerges as a promising approach to address this challenge, facilitating timely updates to the knowledge embedded in LLMs.

Representing knowledge in the form of triples (Meng et al., 2023) or fact chains (Wei et al., 2024a) is a common practice, followed by the process of editing to tailor response of the model to a specific entity. Approximately 80% of real-world knowledge is contained in unstructured formats (Bavota, 2016). This unstructured data is characterized by lengthy content, high noise levels, and complex, comprehensive information, which limits the effectiveness of traditional knowledge editing methods. Consequently, we propose a more challenging and versatile task of editing unstructured textual knowledge, which holds broader practical utility.

Unstructured knowledge editing presents several challenges to previous knowledge editing methods, primarily in the following aspects: (1) previous knowledge editing methods often assume that knowledge exists in MLP layers or knowledge neurons in the form of knowledge triplets (Zhong et al., 2023; Geva et al., 2021; Huang et al., 2023). They modify knowledge triplets by editing or adding additional parameters or models (Mitchell et al., 2022b). However, the experiments conducted in Section 3.1 confirm that structured knowledge triples exhibit non-local characteristics. Furthermore, unstructured knowledge, which possesses a significantly higher knowledge density than structured knowledge, is even less prone to being localized. Consequently, conventional methods for editing previous knowledge are inadequate when it comes to handling tasks related to editing unstructured knowledge. (Meng et al., 2023, 2022) (2) Some knowledge editing methods require locating terms during the editing process, such as the last token of the subject. Otherwise, their effective-

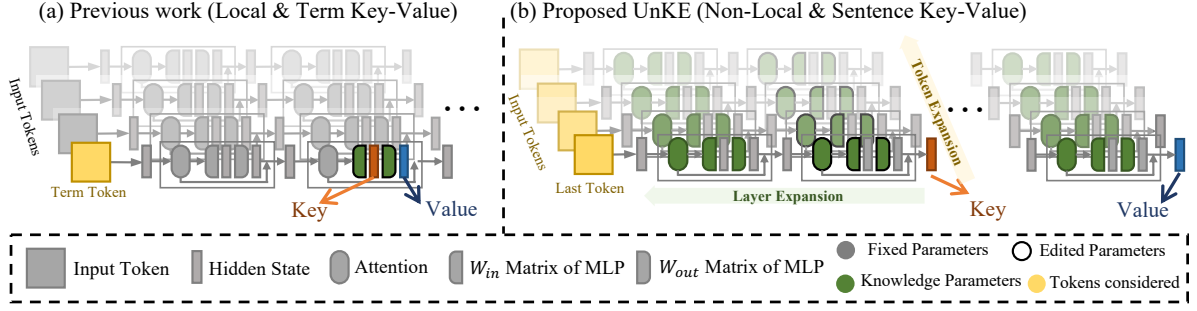


Figure 1: Comparison between UnKE and previous knowledge editing methods. Previous research assumed knowledge is stored as key-value pairs in local MLP layers, editing based on specific term positions like the subject. In contrast, UnKE views knowledge as stored in the global parameters of Transformer layers, considering the positions of all input tokens during editing. UnKE’s editing process involves adjusting parameters in both MLP and attention layers, showing superior unstructured knowledge editing capabilities compared to prior methods.

ness will be significantly reduced, as demonstrated experimentally in Section 3.2. However, locating these terms within unstructured text poses a significant challenge, as illustrated by the case discussed in Table 10.

To bridge this gap, in this paper, we introduce an **Unstructured Knowledge Editing (UnKE)** method that leverages causally driven optimization to edit layer-level key-value pairs. As shown in Figure 1, specifically, we argue that unstructured knowledge is not strictly limited to particular (local) MLP layers or knowledge neurons, but is distributed collaboratively across multiple layers (non-local). To this end, we expand previous hypotheses in two dimensions. Firstly, in the layer dimension, we expand the scope of key-value pairs from MLP layers to Transformer layers (Meng et al., 2023, 2022), and perform edits to Transformer layers, instead of simple MLP neurons. Secondly, in the token dimension, we broaden our focus from individual terms to encompass the entire input sentence. Then, we construct a two-stage optimization process: (1) obtain the key vector that are necessary for editing unstructured knowledge, and (2) employ an optimization method with causal effects to generate this key vector.

To address the lack of a benchmark for editing unstructured knowledge, we develop UnKEBench. UnKEBench is more challenging than existing structured editing benchmarks due to its complexity, which arises from the unstructured nature of target answers and dense knowledge embedded in questions. UnKE significantly outperforms existing baselines across several evaluation metrics within UnKEBench, showcasing its ability to precisely define editing goals for specific questions. Additionally, UnKE demonstrates superior stabil-

ity in both batch and sequential editing scenarios, as well as surpassing strong baseline models for structured knowledge editing.

## 2 Related Works

### Preserving the Original Model Parameters

One category focuses on introducing additional parameters, while the other focuses on involving knowledge in in-context learning (ICL). However, both methods face challenges in efficiently editing a large amount of knowledge within a single model, primarily due to limitations in parameter count and context window length. For adding parameters, SEARC (Mitchell et al., 2022b) utilizes a classifier to differentiate between input that requires editing and input that does not. If editing is necessary, the trained counterfactual model is employed for prediction; otherwise, using the original model. T-Patcher (Huang et al., 2023) incorporates and trains specific neurons in the final feed-forward network layer for the sample that requires editing, e.g. their functionality activated solely when encountering the edited sample. Additionally, (Hartvigsen et al., 2023) proposed GRACE, a life-long model editing method that generates a discrete local editing codebook while preserving the model weights unchanged. While training additional parameters may be effective for editing knowledge triples, their success with unstructured knowledge is limited by the number of parameters. For ICL, IKE (Zheng et al., 2023) utilizes ICL for knowledge editing, while MeLLO (Zhong et al., 2023) enhances multi-hop knowledge editing capabilities by decomposing complex multi-hop problems into sub-problems and integrating them with retrieval techniques. Methods based on ICL face limitations in inference cost and context length especially for

the verbosity, noise, and interdependencies of unstructured knowledge.

**Locate-Then-Edit** Another branch of methods adopts a locate-and-edit two-step approach. Initially, they identify the specific parameters associated with the target knowledge and subsequently modify those parameters directly to effectuate the desired knowledge editing. KN (Dai et al., 2022) introduces the concept of knowledge neurons and utilizes them to incorporate specific factual knowledge without the need for fine-tuning. ROME (Meng et al., 2022) introduces a causal tracking method to identify the layer that requires editing. Subsequently, it employs Rank-One Model Editing to modify the weights of the feedforward layer, thereby updating specific factual associations. MEMIT (Meng et al., 2023) is an enhanced version of ROME, capable of editing knowledge in batches. These methods operate under the assumption that knowledge is stored locally within MLP layers or neurons, which prove inadequate when confronted with unstructured knowledge.

**Others** Additionally, there exist numerous other methods that enable knowledge editing by directly modifying model parameters without the need for explicit positioning. MEND (Mitchell et al., 2022a) introduces auxiliary networks and enables scalable editing by decomposing gradients, thereby facilitating efficient and effective knowledge editing. To enhance the stability and effectiveness of knowledge editing in large language models, StableKE (Wei et al., 2024b) employs additional knowledge for fine-tuning, presenting an approach that brings about significant improvements. As knowledge transitions from a structured to an unstructured format, the process of editing them becomes time-consuming, leading to a degradation in performance.

### 3 Motivation

In this section, we demonstrate through preliminary experiments that the aforementioned assumptions of existing knowledge editing methods are not entirely accurate. These findings, in turn, shed light on the motivations for our proposed approach.

#### 3.1 LLMs Store Knowledge Non-locally

Previous research typically considers knowledge to be stored in specific local parameters of LLMs, and modifying these parameters to achieve knowledge

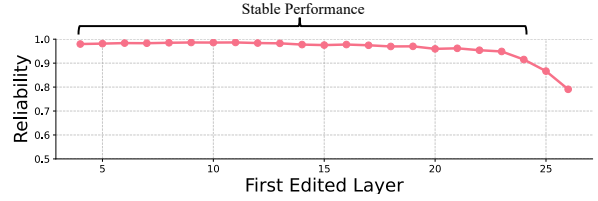


Figure 2: Performance evaluation of MEMIT on the Counterfact dataset. The x-axis indicates the starting layer number for editing, and the number of editing layers is 5. The reliability metric represents the editing success rate.

Table 1: Performance comparison on KEBench: Impact of locating the subject. Ori-Acc and Para-Acc represent the accuracy for the original question and the paraphrased question, respectively. None Subject indicates the last token to locate the question.

Method	Subject		None Subject	
	Ori-Acc	Para-Acc	Ori-Acc	Para-Acc
ROME	77.90	68.40	44.10	23.60
MEMIT	74.80	64.30	37.60	27.10

editing. However, we propose that knowledge in LLMs is distributed non-locally and can be activated through specific reasoning modes. As shown in the Figure 2, we use a typical knowledge editing method, MEMIT, to conduct experiments on the Counterfact dataset (Meng et al., 2022). The results indicate that the editing success rate does not change significantly with the target number of edited layers. This finding demonstrates that knowledge is not confined to a specific layer but rather is stored non-locally. Therefore, the long, noisy, and complex characteristics of unstructured text pose a challenge for traditional methods that edit specific layers.

#### 3.2 Term-driven Optimization Lacks Robustness

Some editing methods for knowledge triples use term-driven optimization strategies. For example, MEMIT and ROME both increase the editing success rate by locating the last token in the subject. As shown in the Table 1, omitting this step causes their performance to drop significantly on KEBench (Wei et al., 2024b). While the subject can be easily located for knowledge triples, it is difficult to accurately determine the best term in unstructured knowledge. Therefore, we believe that this step should be omitted in unstructured knowledge editing, and that editing should be performed directly at the sentence level through the causal effect of autoregressive LLMs.

## 4 UnKE Method

Building on the expanded assumptions, our research addresses two main questions: (1) What do the key-value pairs at the layer level signify? and (2) How can we modify them effectively to achieve the desired editing outcome?

To address the first question, we start by identifying the editing target. We propose that the value vector can be directly decoded into the desired editing target once it passes through the head layer of LLMs. The key vector should be used as the corresponding keys to activate this value vector. Depending on the number of layers, we conceptualize the LLM as comprising two distinct components: a key generator and a value generator, which generate key vectors and value vectors respectively.

For the second question, we establish a two-stage optimization process. First, we obtain the key vector for the target that requires editing (with the value vector computed during the intermediate process). Second, we optimize the key generator to produce this key vector.

### 4.1 Calculating Key Vectors

This section explains the procedure for obtaining the key vector that corresponds to the editing target.

Let  $f_\theta = f_{\theta_1}^1 \circ f_{\theta_2}^2 \circ \dots \circ f_{\theta_l}^l \circ \dots \circ f_{\theta_N}^N$  denote an autoregressive LLM with parameters  $\theta$ , which can be regarded as an  $N$ -layer Transformer decoder.  $\circ$  stands for cascade symbol. For the  $l$ -th layer, we denote it as  $f_{\theta_l}^l$ , where  $\theta_l$  represents the parameters of this layer. We take the  $L$ -th layer as the boundary, and the key generator is represented as  $f_{\theta_k}^{l \leq L} = f_{\theta_1}^1 \circ \dots \circ f_{\theta_L}^L$ , and the value generator  $f_{\theta_v}^{L < l \leq N} = f_{\theta_{L+1}}^{L+1} \circ \dots \circ f_{\theta_N}^N$ .  $\theta_k$  and  $\theta_v$  are parameters of the key generator and the value generator respectively.

For a given question  $q = [q_1, q_2, \dots, q_n]$ , where  $q_i$  represents the  $i$ -th token of the question, and  $n$  represents the number of question tokens,  $f_\theta$  generates text by iteratively sampling from a conditional token distribution  $\mathbb{P}(o_t | q_1, q_2, \dots, q_n)$ , where  $o_t$  represents the  $t$ -th token of the output. We use  $h_q^l = [h_{q,1}^l, h_{q,2}^l, \dots, h_{q,n}^l]$  to represent the hidden state of  $q$  in the  $l$ -th layer. Our ultimate goal is to maximize  $\mathbb{P}(a|q)$  of generating the edit target expressed as unstructured knowledge  $a = [a_1, a_2, \dots, a_m]$ , where  $m$  represents the number of target tokens.

We consider the last token representation of the output from the last layer  $L$  of the key generator as the original key vector  $k = h_{q,n}^L$  for the question  $q$ . The original value vector  $v$  is seen as the output of

the value generator given  $q$ . Our goal is to modify them to obtain the editing target, and the process is denoted as  $(k \rightarrow k^*, v \rightarrow v^*)$ , where  $k^*$  and  $v^* = [v_1, v_2, \dots, v_m]$  represent the key vector and value vector we expect to get. The value vector  $v^*$  can decode the target  $a = \text{softmax}(W_h v^{*T})$  after passing through the head layer, where  $W_h$  represents the parameter matrix in the head layer. Next, we identify the key vector  $k^*$  that can activate this value vector  $v^*$ . Inspired by previous work (Meng et al., 2023), we find  $k^* = h_{q,n}^L + \delta_n$  directly by optimizing the residual vector  $\delta_n$  using gradient descent,

$$k^* = h_n^L + \underset{\delta_n}{\operatorname{argmin}} -\log \mathbb{P}_{f_\theta(h_{q,n}^L \mapsto h_{q,n}^L + \delta_n)}(a|q). \quad (1)$$

$f_\theta(h_{q,n}^L \rightarrow h_{q,n}^L + \delta_n)$  means that we replace the hidden state  $h_{q,n}^L$  (also be expressed as original key vector  $k$ ) with  $k^*$ . Optimizing Eq. 1 to a small enough value means that if we can get  $k^* = f_{\theta_k}^{l \leq L}(q_1, q_2, \dots, q_n)$ , then we can decode the target  $a$ .

### 4.2 Optimizing the Key Generator

After obtaining the desired expression form of  $k^*$ , our second goal is to optimize the key generator  $f_{\theta_k}^{l \leq L}$  to produce the key vector  $k^*$  on the  $n$ -th hidden state of layer  $L$ .

$f_{\theta_k}^{l \leq L}$  store a large number of key vectors  $K_0 = [k_1 | k_2 | \dots | k_E]$  during the pre-training process, which can be activated by specific inputs  $D_0 = [d_1 | d_2 | \dots | d_E]$  to generate corresponding value vectors  $V_0$ ,

$$f_{\theta_k}^{l \leq L} \triangleq \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^E \| f_{\theta}^{l \leq L}(d_i) - k_i \|^2, \quad (2)$$

where  $E$  represents the number of knowledge key-value pairs introduced during pre-training, which can be regarded as  $+\infty$ . Therefore during the optimization process we should minimize the parameter changes of  $f_{\theta_k}^{l \leq L}$  and produce a new key generator  $f_{\theta'_k}^{l \leq L}$  that can generate the new key  $k^*$ ,

$$f_{\theta'_k}^{l \leq L} \triangleq \underset{\theta}{\operatorname{argmin}} \left( \sum_{i=1}^E \| f_{\theta}^{l \leq L}(d_i) - k_i \|^2 + \| f_{\theta}^{l \leq L}(q) - k^* \|^2 \right), \quad (3)$$

where  $\theta'_k$  represents the updated parameters. This approach minimizes the impact of adding new key-value pairs on the original key-value pairs. In par-



ticular, we are able to edit a batch of  $u$  unstructured knowledge at one time, which we denote by  $K_1 = [k_1^* | k_2^* | \dots | k_u^*]$ . Eq 3 can be changed to,

$$f_{\theta'_k}^{l \leq L} \triangleq \underset{\hat{\theta}}{\operatorname{argmin}} \left( \sum_{i=1}^E \| f_{\hat{\theta}}^{l \leq L}(d_i) - k_i \|^2 + \sum_{j=1}^u \| f_{\hat{\theta}}^{l \leq L}(q_j) - k_j^* \|^2 \right). \quad (4)$$

To avoid the addition of new keys affecting the generation of original keys, we only optimize the last layer of the key encoder  $f_{\theta_L}^L$ . In order to optimize Eq 4, we randomly select a number  $C$  of instruction fine-tuning samples to simulate the knowledge  $f_{\theta_L}^L$  learned during pre-training. Assuming that  $i$ -th instruction fine-tuning sample can be represented as  $t^i = [t_1^i, t_2^i, \dots, t_P^i]$ , where  $P$  represents the number of  $i$ -th instruction fine-tuning sample tokens, which is regarded as encoding the key vector  $k_t^i = [k_{t,1}^i, k_{t,2}^i, \dots, k_{t,P}^i]$ . Before performing optimization, we first calculate the key vector  $k_{t,p}^i$  corresponding to the  $p$ -th token in  $i$ -th instruction fine-tuning sample. Considering the causal properties of autoregressive LLM, for each key we need to consider its context,

$$k_{t,p}^i = f_{\theta_L}^L(\text{causal\_att}(h_{t,1}^{i,L-1}, \dots, h_{t,p}^{i,L-1})), \quad (5)$$

where  $\text{causal\_att}$  represents the attention mechanism with causal mask, and  $h_{t,p}^{i,L-1}$  represents the vector of the  $p$ -th token of the  $i$ -th instruction fine-tuning sample in the  $l$ -th layer. We use  $f_{\theta_L, \text{ca}}^L(\cdot)$  to represent  $f_{\theta_L}^L(\text{causal\_att}(\cdot))$ . By incorporating causal effects, we ensure that the generation of key vectors considers the full context, which is crucial, especially for lengthy and information-rich unstructured texts. This leads us to our ultimate optimization objective, which is to

$$f_{\theta'_L}^L = \underset{\hat{\theta}}{\operatorname{argmin}} \left( \underbrace{\sum_{i=1}^C \sum_{p=1}^P \| f_{\hat{\theta}, \text{ca}}^L(h_{t, \leq p}^{i,L-1}) - k_{t,p}^i \|^2}_{\text{Key Preservation Loss}} + \underbrace{\sum_{j=1}^u \sum_{i=1}^{n-1} \| f_{\hat{\theta}, \text{ca}}^L(h_{q, \leq i}^{j,L-1}) - k_{q,i}^j \|^2}_{\text{Key Paraphrase Loss}} + \underbrace{\sum_{j=1}^u \| f_{\hat{\theta}, \text{ca}}^L(h_{q, \leq n}^{j,L-1}) - k_q^{*,j} \|^2}_{\text{Key Learning Loss}} \right), \quad (6)$$

where  $h_{t, \leq p}^{i,L-1}$  represents tokens less than or equal to  $p$  in the  $i$ -th instruction fine-tuning sample, and

$h_{q, \leq i}^{j,L-1}$  represents tokens less than or equal to  $i$  in the  $j$ -th question to be edited. The Key Preservation Loss ensures that the key generator retains the keys stored during pre-training, enabling the preservation of original knowledge. Key Paraphrase Loss learns the semantics of the question and ensures that the correct key vector  $k_q^{*,j}$  can be generated even under paraphrase questions. Additionally, the Key Learning Loss facilitates the key generator in acquiring new keys, activating the corresponding patterns in the value generator, and achieving the desired editing target. The optimization of the key generator is accomplished through gradient descent, optimizing Eq 6.

## 5 Experiments

We first introduce the experimental setup (§ 5.1) and baseline approaches for comparison (§ 5.2). Then, we evaluate model performance on both unstructured knowledge editing (§ 5.3) and structured knowledge editing (§ 5.5).

### 5.1 Experimental Setup

#### 5.1.1 Dataset

To the best of our knowledge, there is no dedicated benchmark for knowledge editing in unstructured texts. Due to space limitations, we detail the existing knowledge editing benchmarks in Appendix A. To establish a benchmark for unstructured knowledge editing, we develop UnKEBench.

The unstructured texts are notably lengthy and contain knowledge that extends beyond simple knowledge triples or linear fact chains. To effectively manage this complexity, we have structured our approach into three distinct phases.

1. We employ meticulously crafted instructions to guide ChatGPT in formulating the most appropriate question  $Q$  for each text  $A$ , thus creating an unstructured knowledge pair  $(Q, A)$ .
2. To refine our evaluation mechanism, we use detailed instructions to prompt ChatGPT to generate a paraphrased version of each original question, denoted as  $Q_p$ , for every original question  $Q$ .
3. We leverage knowledge decomposition strategies and engage ChatGPT to produce multiple sub-question and sub-answer pairs  $(Q_s^i, A_s^i)$  for each unstructured knowledge text, where  $i$  represents the specific sub-question or answer.

Details and examples of constructing UnKEBench are provided in the Appendix B.

### 5.1.2 Evaluation Metrics

Our evaluation framework for unstructured knowledge editing mirrors the complexity of the task by integrating three critical dimensions: word-level overlap, semantic similarity, and factual correctness.

- **Word-level overlap** metrics, including BLEU (Papineni et al., 2002) and various ROUGE scores (Lin, 2004) (ROUGE-1, ROUGE-2, and ROUGE-L), provide insight into the lexical and n-gram alignment between the model-generated text and the target answers, based on both the original and paraphrased questions. These metrics are fundamental in assessing the surface-level accuracy of the edited content.
- **Semantic similarity.** As word-level overlap metrics alone are insufficient for capturing the nuanced understanding a model must exhibit. To bridge this gap, we evaluate semantic similarity by leveraging an embedding encoder (specifically, the all-MiniLM-L6-v2 model) to quantify the depth of comprehension of the model of the text, ensuring a balanced evaluation that transcends mere lexical matching.
- **Factual correctness.** To gauge generalization capabilities, we involve an innovative measure, FactScore (Min et al., 2023), which assesses precision of LLMs in handling sub-questions and their corresponding answers. This step is crucial, as it evaluates ability of LLMs to maintain semantic integrity and factual accuracy in its responses, despite the inherent variability in language expression.

## 5.2 Base Models and Baseline Methods

We conduct experiments on two autoregressive models, LLaMA-2-7B-Chat and Qwen1.5-7B-Chat. For baselines, we first compare the fine-tuning method **FT-L**, which targets specific layers, with **FT-A**, which fine-tunes all layers. Additionally, we assess two robust baseline models, **ROME** and **MEMIT**, focusing on their locating and editing capabilities. Lastly, we evaluate the hypernetwork-based model editing method, **MEND**.

## 5.3 Unstructured Knowledge Editing Experiments on UnKEBench

We conduct a comprehensive evaluation of various baseline methods and our newly proposed UnKE method on the UnKEBench benchmark. The specific results presented in Table 2. Traditional fine-tuning methods, including FT-L and FT-A, have long exhibited significant limitations when tasked with structured knowledge editing. As anticipated, their performance on UnKEBench is underwhelming, with all evaluation metrics falling short of those achieved by dedicated knowledge editing approaches. Methods employing a Locate-Then-Edit paradigm, such as ROME and MEMIT, despite previously demonstrating satisfactory editing success rates on certain structured benchmarks, underperform on the UnKEBench dataset, particularly in terms of lexical and semantic similarity when compared to UnKE. UnKE demonstrates exceptional performance, surpassing other models in lexical and semantic similarity metrics, which confirms its ability to accurately capture and reproduce the intended editing objectives—a feat that other models do not achieve. For more examples of generated cases, please refer to the Appendix C. Regarding the detailed evaluation metric of FactScore, UnKE achieves a score of 38.82, outperforming other strong baseline models, yet highlighting that there is still room for further improvement.

We also extend our unstructured knowledge editing experiments to utilize Qwen1.5-7b-Chat as base model and compare against MEMIT. The results indicate that our approach outperforms MEMIT across multiple evaluation dimensions significantly. These experiments, conducted on models with varying architectures, demonstrate the robust transferability of our proposed UnKE method.

## 5.4 Human Evaluation

Considering the complexity and challenges involved in automatically evaluating unstructured knowledge editing, we conduct additional manual evaluation experiments. Due to the high cost of human evaluation, we randomly select 36 samples from a pool of 1000 samples generated by each method. We employ three annotators who are familiar with knowledge editing tasks for human evaluation and instruct them to evaluate the edited generated text along three dimensions: semantic correctness, similarity, and coherence on a scale

Table 2: Unstructured knowledge editing performance with different methods. During the editing process, we set the batch size to 1. With each editing instance, the parameters of the modified model are rebuilt. The decoding process employs a temperature of 0.001. To ensure fair comparison, the 7-th layer of parameters of the model is specifically targeted for editing across FT-L, ROME, and UnKE. The figures to the left and right of the '/' symbol denote the evaluation outcomes for output of the model in response to the original and paraphrased questions, respectively.

Method	Word-level Overlap				Semantic Similarity	Factual Correctness
	BLEU	Rouge-1	Rouge-2	Rouge-L	Bert-Score	FactScore
<i>Based on LLaMA-7B-Chat</i>						
FT-A	1.01 / 1.02	0.92 / 0.92	0.01 / 0.01	0.92 / 0.92	2.56 / 2.58	8.74
FT-L	6.14 / 5.52	7.55 / 6.78	1.37 / 1.28	7.26 / 6.53	11.63 / 10.16	15.69
ROME	47.31 / 41.64	28.89 / 20.93	45.05 / 39.06	38.71 / 33.42	76.52 / 74.29	24.44
MEMIT	35.79 / 33.19	43.55 / 41.39	23.11 / 19.89	40.96 / 38.81	75.90 / 74.46	26.39
MEND	24.10 / 29.23	45.36 / 45.06	31.75 / 29.33	44.05 / 43.77	69.99 / 64.71	24.17
UnKE	<b>81.20 / 73.59</b>	<b>83.27 / 75.64</b>	<b>76.85 / 66.45</b>	<b>82.44 / 74.53</b>	<b>93.29 / 91.71</b>	<b>38.82</b>
<i>Based on Qwen1.5-7B-Chat</i>						
MEMIT	48.89 / 48.71	49.50 / 48.18	34.59 / 31.50	47.55 / 46.04	74.72 / 76.82	17.81
UnKE	<b>92.85 / 75.66</b>	<b>91.74 / 72.68</b>	<b>88.19 / 60.59</b>	<b>91.40 / 70.44</b>	<b>96.51 / 90.40</b>	<b>40.08</b>

Table 3: Performance on human evaluation and structured knowledge editing performance on KEBench. Ori-ACC and Para-ACC represent the accuracy for the original question and the paraphrased question, respectively.

Method	Correctness	Similarity	Coherence
FT-A	1.06	1.47	1.47
FT-L	1.17	1.00	1.31
ROME	3.39	3.59	3.64
MEMIT	3.25	3.70	3.72
UnKE	<b>4.78</b>	<b>4.72</b>	<b>4.70</b>

(a) Human Evaluations

Method	Ori-Acc	Para-Acc
FT-A	6.30	6.60
FT-L	14.70	12.10
ROME	77.90	68.40
MEMIT	74.80	64.30
UnKE	<b>87.60</b>	<b>70.40</b>

(b) Structured Knowledge Editing.

of 1-5, with 1 denoting "very low" and 5 representing "very high". The scores are then averaged to derive the final human evaluation results. The evaluation results, presented in Table 3a, reflect the collective assessments by the hired professionals. The inter-annotator agreement is 0.57 in Fleiss'  $\kappa$ , which means a moderate agreement.

The experimental results provide strong evidence of the high consistency between the automatic evaluations and human evaluations. UnKE stands out as the leader across all three dimensions. In contrast, the other baseline models frequently exhibit subpar performance in terms of semantic correctness, highlighting their limited ability to effectively edit unstructured knowledge.

## 5.5 Performance in Structured Knowledge Editing

To validate the capability of UnKE in editing knowledge triples, we conduct experiments on KEBench (Wei et al., 2024b), a benchmark that evaluates whether the model accurately produces the desired target answer after editing. The results

presented in Table 3b demonstrate that UnKE surpasses strong baseline models in terms of Ori-Acc and Para-Acc metrics, exhibiting improvements of 9.7 points and 2.0 points, respectively. When comparing the results with UnKEBench, the improvement of UnKE over the strong baseline may not be as pronounced. However, this outcome is anticipated since UnKE primarily targets complex and lengthy unstructured knowledge editing tasks, making it less conspicuous in simpler structured knowledge editing tasks.

## 5.6 Robustness Analysis on Batch Editing and Sequential Editing

To evaluate the robustness of UnKE in unstructured knowledge editing, we assess its batch editing capabilities (as shown in Table 4) and sequential editing performance (as presented in Figure 3) using the UnKEBench dataset. In the batch editing assessment, we observe that as the batch size increases, the model's performance on the original task remains relatively stable, indicating the robustness of UnKE's batch editing capabilities. However, there

Table 4: Comparison of different batch sizes. We conducted experiments on UnKE using the LLaMA2-7B-Chat model, with the decoding temperature set to 0.001.

Batch Size	Semantic Similarity	Lexical Similarity				Accuracy
	Bert-Score	BLEU	Rouge-1	Rouge-2	Rouge-L	Fact-Score
$2^0$	93.29 / 91.71	81.20 / 73.59	83.27 / 75.64	76.85 / 66.45	82.44 / 74.53	38.82
$2^1$	93.79 / 90.77	81.79 / 72.34	83.64 / 74.05	77.17 / 64.22	82.77 / 72.90	36.15
$2^2$	93.29 / 89.66	81.63 / 69.35	83.60 / 70.99	77.28 / 60.32	82.81 / 69.70	34.68
$2^3$	93.72 / 86.48	83.01 / 64.36	84.34 / 65.25	78.28 / 53.07	83.61 / 63.84	36.20
$2^4$	93.43 / 84.32	82.06 / 60.63	83.46 / 62.26	77.11 / 49.18	82.67 / 60.73	35.25
$2^5$	93.47 / 82.40	81.91 / 57.61	83.65 / 58.87	77.32 / 44.91	82.83 / 57.25	34.52
$2^6$	93.04 / 82.58	81.58 / 57.05	82.90 / 58.02	76.38 / 43.58	82.83 / 57.25	34.23

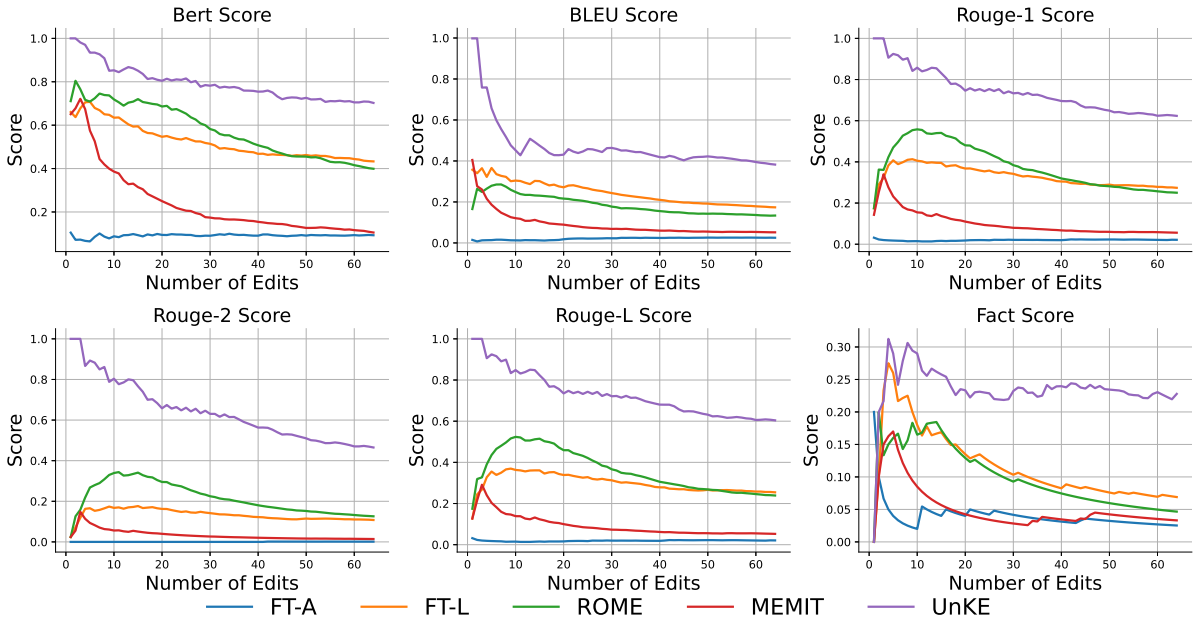


Figure 3: Performance in sequential editing. We select the first 64 samples in the UnKEBench data set for sequential editing experiments.

is a slight reduction in performance on paraphrased questions, which is expected. The simultaneous optimization of a larger number of keys marginally diminishes the model’s generalization ability for paraphrased questions. For sequential editing, we find that the performance of all methods declines as the number of edits increases. Nevertheless, UnKE exhibits the highest stability compared to other baseline methods, demonstrating its robustness in sequential editing scenarios. These findings underscore the effectiveness of UnKE in handling both batch and sequential editing tasks, highlighting its potential as a promising approach for unstructured knowledge editing.

## 6 Conclusions

We address the limitations of existing knowledge editing benchmarks, which primarily focus on

structured knowledge triples, by introducing UnKEBench, the first benchmark for unstructured knowledge editing. To successfully edit unstructured knowledge, we propose UnKE, an unstructured knowledge editing method, which incorporates layer-level knowledge key-value pairs and layer-level knowledge editing parameters, enabling it to effectively represent and edit unstructured knowledge with ease. Experimental results on UnKEBench demonstrate the superior performance of UnKE, significantly surpassing powerful baseline models on various evaluation metrics. Robustness analysis experiments confirm that UnKE possesses the ability to perform both batch and sequential editing. Additionally, UnKE also compares favorably with other strong baseline models on structured knowledge editing benchmarks.



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## A Related Work on Knowledge Editing Benchmarks

Previous knowledge editing datasets are composed in the form of triples or fact chains. The two prominent datasets are ZsRE (Levy et al., 2017) and COUNTERFACT (Meng et al., 2022). ZsRE utilizes back translation to generate paraphrase questions, while COUNTERFACT focuses on constructing counterfactual data. The MQuAKE dataset (Zhong et al., 2023), which serves as a multi-hop knowledge editing dataset, is utilized to assess the impact of knowledge editing on intricate knowledge chains. KEBench (Wei et al., 2024b) performs a comprehensive evaluation of the stability of different knowledge editing methods using a tree-structured dataset. Furthermore, (Zhang et al., 2024) introduced KnowEdit, an integrated evaluation benchmark that incorporates popular knowledge editing datasets to comprehensively assess various knowledge editing technologies. Simultaneously, numerous efforts (Wei et al., 2024a; Wang et al., 2023a,b) have been made to construct multilingual datasets aiming to evaluate the generalizability of knowledge editing methods across diverse languages. Eva-KELLM (Wu et al., 2023) is a benchmark for evaluating document-level knowledge. However, it merely extends a specific knowledge triple to a document and fails to account for the characteristics of unstructured knowledge.

## B Implementation Details of Constructing UnKEBench

LLMs develop significant parameter memories after undergoing comprehensive pre-training on extensive corpora. To ensure that these parameter memories do not inherently encompass editing objectives, we curate a dataset consisting of 1000 counterfactual unstructured texts. These texts are sourced from ConflictQA (Xie et al., 2024), a benchmark specifically designed to distinguish between the parameter memory of the LLM and its counter-memory. This strategy is essential to prevent the model from merging the knowledge gained during pre-training with that obtained from editing tasks. Moreover, it addresses the critical challenge of discerning whether the model has learned target knowledge during the training phase or the editing process, thus maintaining a clear demarcation between pre-training learning and editing objectives. Table 6 and 7 show the instructions for using ChatGPT (gpt-3.5-turbo) to generate original

Table 5: Comparison of different decoding temperatures. We conduct experiments on UnKE using the LLaMA2-7B-Chat model, and the batch size is set to 1.

Temperature	Semantic Similarity	Lexical Similarity			
	Bert-Score	BLEU	Rouge-1	Rouge-2	Rouge-L
0.1	93.44 / 92.12	81.84 / 71.38	84.02 / 77.29	77.21 / 67.88	83.19 / 76.10
0.3	92.70 / 91.32	81.98 / 71.52	84.08 / 77.43	77.12 / 68.12	83.17 / 76.25
0.5	92.54 / 90.99	79.98 / 71.06	81.31 / 76.49	73.31 / 66.84	80.27 / 75.22
0.7	92.49 / 90.27	79.29 / 69.66	80.65 / 74.95	72.57 / 64.76	79.54 / 73.58

and rephrased questions for unstructured text.

## C Case Analysis of ROME, MEMIT and UnKE

Table 10 shows the generation cases of three different methods: ROME, MEMIT and UnKE. The methods of editing local key-value pairs, namely ROME and MEMIT, limit capabilities when it comes to complex unstructured knowledge editing tasks. These methods can only remember a small set of editing goals and are unable to fully retell the editing objectives. In contrast, UnKE exhibits greater proficiency in handling such tasks and is capable of conveying the editing goals.

## D Impact of Decoding Temperature on Model Performance

The ultimate optimization goal of UnKE is to find the value vector  $v^*$  that can decode the target  $a = \text{softmax}(W_h v^{*T})$ . This corresponds to greedy decoding among the decoding methods. However top-p or top-k decoding is more commonly used than greedy decoding. Therefore, we explored the impact of different decoding temperatures on UnKE, and the results are shown in the Table 5. The results show that UnKE still exhibits stable performance under different decoding temperatures, which proves that UnKE optimizes the semantics of unstructured knowledge rather than rote memorization.

## E Experiment Details

Except for UnKE, we use EasyEdit <sup>1</sup> to implement all other editing methods, including fine-tuning. For all other baselines, except for the necessary modifications that need to be applied to UnKEBench, we use the official default hyperparameters, which can be easily reproduced in the official

library. The optimizer type used when it comes to gradient descent is Adam. The following are their important hyperparameter configuration contents.

**Fine-tuning** Fine-tuning consists of two variants: FT-L and FT-ALL, with the only distinction being the number of layers involved in parameter updates. The maximum length is set to 1024, and a learning rate of  $5 \times 10^{-4}$  is utilized. Each sample undergoes 25 optimization steps. The layer where FT-L parameters are updated is layer 7, which is consistent with UnKE.

**ROME and MEMIT** The primary distinction between ROME and MEMIT lies in the number of editing layers. ROME focuses on editing the layer 7, while MEMIT targets the layers [4,5,6,7,8]. Both approaches undergo 25 optimization steps, utilizing a learning rate of  $5^{-1}$ , a weight attenuation coefficient of  $1 \times 10^{-3}$ , and a KL factor of 0.0625. Before the editing process, approximately 100,000 Wikipedia samples need to be computed, which is a highly time-consuming task.

**MEND** MEND enables concurrent edits by accumulating gradients from all edit examples and passing them through the hypernetwork simultaneously. It calculates parameter layers 29, 30, and 31 and utilizes a learning rate of  $1 \times 10^{-4}$ . Due to the presence of numerous hyperparameters, it is advisable to refer to the official website or code library for detailed information.

**UnKE** UnKE employs a two-stage structuring process. In the first stage, the learning rate is set to  $5e-1$ , with 25 optimization steps and a weight attenuation coefficient of  $1e-3$ . In the second stage, the learning rate is set to  $2e-4$ , and 50 optimization steps are performed. All experiments conducted on UnKE in this article focus on optimizing layer 7. During each optimization iteration, an additional 20 samples are randomly selected from the alpaca

<sup>1</sup><https://github.com/zjunlp/EasyEdit>

<b>System:</b>
You are given a text and asked to come up with a question that best fits it.
<b>User:</b>
George Rankin has been actively involved in politics for over a decade. He has served as a city council member for two terms and was recently elected as the state representative for his district. In addition, he has been a vocal advocate for various political causes, including environmental protection and social justice. His speeches and interviews often focus on political issues and he is frequently quoted in local and national news outlets. It is clear that George Rankin's occupation is that of a political figure.
<b>Assistant:</b>
What is George Rankin's occupation?

Table 6: Demonstrating the application of ChatGPT (gpt-3.5-turbo) in generating a question about unstructured text.

<b>System:</b>
You are given a question and asked to come up with a semantically similar paraphrase question.
<b>User:</b>
What is George Rankin's occupation?
<b>Assistant:</b>
What does George Rankin do for a living?

Table 7: Demonstrating the application of ChatGPT (gpt-3.5-turbo) in generating a paraphrased question from a raw question.

Table 8: Comparison of running time of each method. Time is in hours.

Method	Time	Method	Time
FT-L	24	ROME	21
FT-A	31	MEMIT	27.75
MEND	38	UnKE	10.5

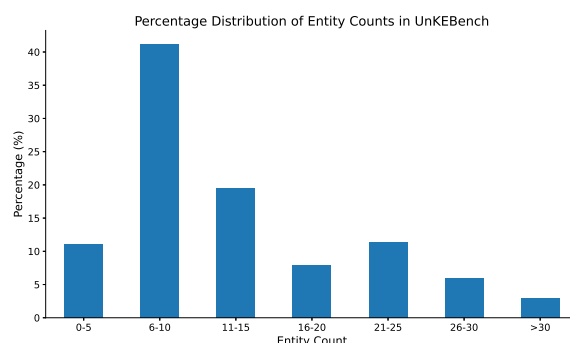


Figure 4: The X-axis represents the number of entities contained in unstructured text, while the Y-axis indicates the proportion of sentences containing that number of entities among all sentences.

instruction fine-tuning data <sup>2</sup>. It is important to note that this number is significantly less than what is required by ROME and MEMIT.

**Time costs** We present the runtime of each knowledge editing method on UnKEBench. It is important to note that our evaluation approach differs from the EasyEdit framework. Instead, we edit a sample and subsequently allow the model to generate the corresponding problem results for evaluation. This process may take slightly longer. Additionally, ROME and MEMIT require additional time for calculating Wikipedia knowledge. MEND adds the time to calculate the one-stage model. Please refer to the Table 8 for detailed results. All experiments can be completed on an A800-80G graphics card.

<sup>2</sup>[https://github.com/tatsu-lab/stanford\\_alpaca](https://github.com/tatsu-lab/stanford_alpaca)

## F The basic statistics of UnKEBench

As shown in Figure 4, only 10% of the sentences contain 0-5 entities, which is a common range for structured text editing tasks. In contrast, over 90% of the sentences contain more than 5 entities, highlighting the inherent complexity of unstructured text.

## G Broader Impacts

UnKE offers the advantage of timely updating outdated knowledge in LLMs, thereby reducing costs for developers and eliminating the need for



<p><b>System:</b>  You are asked to generate some short question-answer pairs based on the specified text. These question-answer pairs mainly ask questions about the knowledge entities in the text, and the answers should be the knowledge entities being asked.</p> <p><b>User:</b>  George Rankin has been actively involved in politics for over a decade. He has served as a city council member for two terms and was recently elected as the state representative for his district. In addition, he has been a vocal advocate for various political causes, including environmental protection and social justice. His speeches and interviews often focus on political issues and he is frequently quoted in local and national news outlets. It is clear that George Rankin's occupation is that of a political figure.</p> <p><b>Assistant:</b>  Question: How long has George Rankin been involved in politics?  Answer: Over a decade.  Question: What political positions has George Rankin held?  Answer: City council member and state representative.  Question: What causes has George Rankin advocated for?  Answer: Environmental protection and social justice.  Question: What is George Rankin's occupation?  Answer: A political figure.</p>
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Table 9: Demonstrating the application of ChatGPT (gpt-3.5-turbo) in generating some short question-answer pairs based on the unstructured text.

resource-intensive pre-training or fine-tuning steps. However, it is important to acknowledge the potential misuse of UnKE by malicious actors who may attempt to inject harmful information into LLMs. To mitigate this risk, a knowledge detection system can be employed to identify and prevent the inclusion of malicious content.

**Question :** What were Charles Strachey's main contributions to British politics and law during the 19th century?

**Text:** Charles Strachey, 4th Baron O'Hagan was a prominent political figure in the United Kingdom during the 19th century. He served as a Member of Parliament for the Liberal Party from 1868 to 1874, representing the constituency of Nottingham. During his time in Parliament, he was known for his advocacy of social reform and his support for the rights of workers. In addition to his political career, Strachey was also a respected lawyer and judge, serving as a Queen's Counsel and a Justice of the Peace. His contributions to British politics and law have been widely recognized, and he remains an important figure in the country's history.

**UnKE Prediction :** Charles Strachey, 4th Baron O'Hagan was a prominent political figure in the United Kingdom during the 19th century. He served as a Member of Parliament for the Liberal Party from 1868 to 1874, representing the constituency of Nottingham. During his time in Parliament, he was known for his advocacy of social reform and his support for the rights of workers. In addition to his political career, Strachey was also a respected lawyer and judge, serving as a Queen's Counsel and a Justice of the Peace. His contributions to British politics and law have been widely recognized, and he remains an important figure in the country's history.

**ROME Prediction :** Charles Strachey was a prominent British politician and lawyer who made significant contributions to the country's political and legal landscape during the 19th century. Here are some of his key contributions: 1. Parliamentary Reform: Strachey was a strong advocate for parliamentary reform and played a key role in the passage of the Reform Act of 1832. This act expanded the franchise and redrew electoral boundaries, giving more people the right to vote and increasing the representation of the working class in Parliament. 2. Legal Reform: Strachey was also a leading figure in the legal profession and was instrumental in the passage of the Law Reform Act of 1832. This act aimed to modernize the law and reduce the complexity of legal proceedings, making it easier for .....

**MEMIT Prediction:** Charles Strachey (1796-1867) was a prominent British lawyer and politician who made significant contributions to British politics and law during the 19th century. Here are some of his main contributions: 1. Legal Reforms: Strachey was a strong advocate for legal reform and was instrumental in the passage of the Law Amendment Act of 1870, which established the office of Law Society Council and paved the way for the modernization of the legal profession. He also played a key role in the establishment of the Incorporated Law Society of Scotland. 2. Parliamentary Reforms: Strachey was a member of the House of Commons and served as a vocal advocate for parliamentary reform. ....

Table 10: This table presents the problems and their corresponding unstructured text after editing. It can be observed that the predicted text generated by UnKE is almost identical to the original text. However, the texts generated by methods like ROME and MEMIT only edit a few key knowledge points such as 'political' and 'parliamentary reform', while the detailed descriptions of these knowledge points are almost entirely incorrect.