

QueueEDIT: Structural Self-Correction for Sequential Model Editing in LLMs

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Abstract

Recently, large language models (LLMs) have demonstrated impressive results but still suffer from hallucinations. Model editing has been proposed to correct factual inaccuracies in LLMs. A challenging case is sequential model editing (SME), which aims to rectify errors continuously rather than treating them as a one-time task. During SME, the general capabilities of LLMs can be negatively affected due to the introduction of new parameters. In this paper, we propose a queue-based self-correction framework (QueueEDIT) that not only enhances SME performance by addressing long-sequence dependency but also mitigates the impact of parameter bias on the general capabilities of LLMs. Specifically, we first introduce a structural mapping editing loss to map the triplets to the knowledge-sensitive neurons within the Transformer layers of LLMs. We then store the located parameters for each piece of edited knowledge in a queue and dynamically align previously edited parameters. In each edit, we select queue parameters most relevant to the currently located parameters to determine whether previous knowledge needs realignment. Irrelevant parameters in the queue are frozen, and we update the parameters at the queue head to the LLM to ensure they do not harm general abilities. Experiments show that our framework significantly outperforms strong baselines across various SME settings and maintains competitiveness in single-turn editing. The resulting LLMs also preserve high capabilities in general NLP tasks throughout the SME process.¹

1 Introduction

Recently, large language models (LLMs) have become the foundational infrastructure of modern NLP (Zheng et al. 2022; Blinova et al. 2023). However, LLMs occasionally generate undesirable outputs (Basta, Costa-jussà, and Casas 2021; An et al. 2023) and tend to produce hallucinations (Shi et al. 2023; Tam et al. 2023), creating content that appears plausible but lacks factual support. Although fine-tuning models with updated knowledge offers a direct solution, it is often impractical due to excessive time requirements (Hübötter et al. 2025; Kim et al. 2025; Krishna et al. 2025). To address these issues, there is increasing interest in incorporating knowledge into LLMs via model editing, which directly adjusts a small subset of parameters (Madaan et al. 2022; Fang et al. 2025).

In the literature, previous approaches broadly fall into three categories: Modifying Parameters, Adding Extra Parameters, and Retrieving Data. (1) *Modifying Parameters* approaches modify one or a batch of knowledge triples at a time by editing LLM parameters using meta-learning (Cao, Aziz, and Titov 2021; Mitchell et al. 2022a) or locate-then-edit techniques (Hartvigsen et al. 2022; Meng et al. 2022, 2023). These methods involve locating the neurons in FFN layers corresponding to the edited data and updating these parameters. (2) *Adding Extra Parameters* methods augment LLMs with supplementary neurons for each edit, thus bypassing alterations to the original parameters (Mitchell et al. 2022b; Huang et al. 2023; Zhang et al. 2024). Here, parameter updates are not achieved through backpropagation but rather through extra modules associated with each fact. While these methods quickly fix mistakes, previously edited parameters relevant to the current edit are not updated simultaneously. (3) *Retrieving Data* approaches retrieve external information related to knowledge triplets and concatenate it into the input to form the final editing data (Han et al. 2023; Jiang et al. 2024; Chen et al. 2024). However, continuous retrieval and concatenation can lead to a rapid increase in the length of LLM input, resulting in longer inference time (Li et al. 2023; Liu et al. 2024). Additionally, as the number of edits increases, outdated editing information can cause incorrect answers, negatively affecting LLM performance due to knowledge bias. In Figure 1, when the current editing instance “Donald Trump” is ready to be updated, parameters related to previous edits should be adjusted accordingly. Otherwise, the subsequent question about the “USA President’s wife” will still yield the incorrect answer “Jill Biden.”

In this paper, we propose a queue-based self-correction framework named QueueEDIT. This framework performs knowledge editing for each triplet while simultaneously adjusting specific parameters in FFNs that were previously updated, aiming to maintain SME performance and preserve the general capabilities of LLMs. The key techniques of QueueEDIT are introduced as follows:

Structural Mapping Editing. To more accurately update the knowledge of the current edit to specific FFN layers (Meng et al. 2022; Fang et al. 2025), we map the

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¹Source code will be released upon paper acceptance.

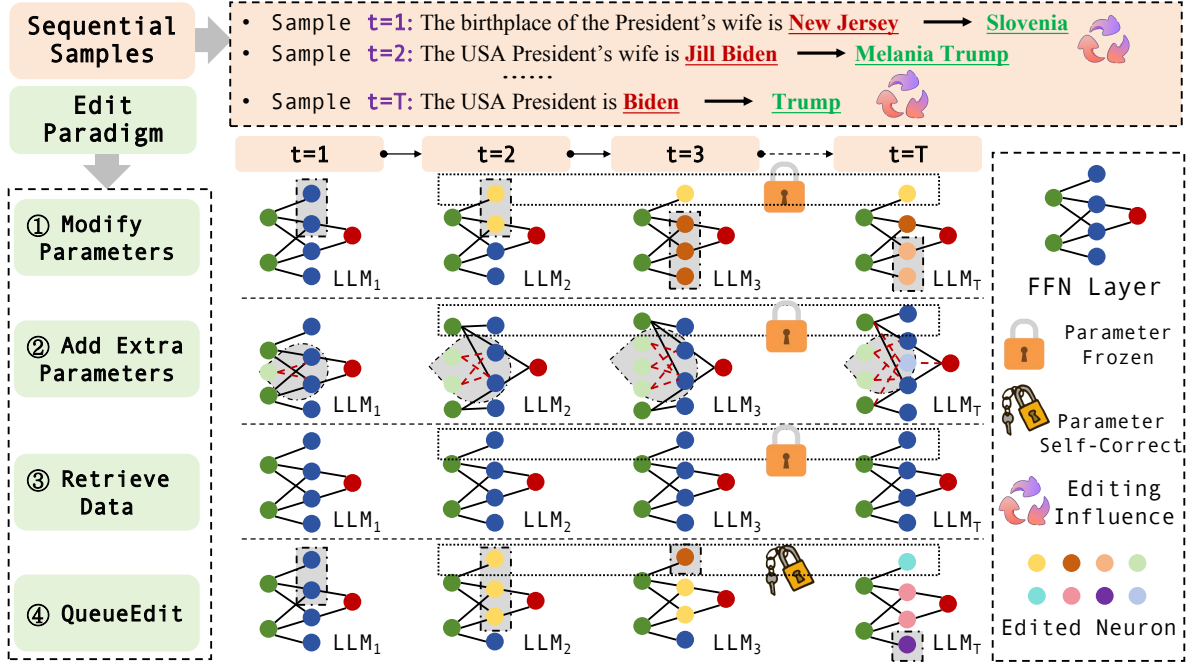


Figure 1: Comparison between SME methods. Modifying Parameters and Adding Extra Parameters approaches change parameters at specific positions in FFN layers without making corresponding adjustments for relevant edits. Retrieving Data methods focus solely on external data for editing knowledge triples. QueueEDIT not only dynamically updates parameters associated with previous edits but also ensures the general capabilities of LLMs.

triplets (i.e., $\langle s, r, o \rangle^2$) to knowledge-sensitive positions in FFN layers. This approach enhances the response of internal activation parameters compared to previous works that disregarded the structural semantics of knowledge triplets (Mitchell et al. 2022a; Mishra et al. 2024). Previous methods utilized both the “relation” and “object” to learn representations for gradient feedback, overlooking the original structure of the knowledge triplets. In this paper, we map the subject, relation, and object in the editing data to the first MLP matrix, the second MLP matrix, and the gradient backpropagation representation in the Transformer’s FFN layer, respectively. Specifically, the “relation”, originally viewed as a bridge connecting the semantic knowledge of subject and object entities (Bordes et al. 2013; Wang et al. 2014), is independently mapped to the second parameter matrix in the FFN layer. We then design a structural loss to update the parameters via the triple’s representations, enhancing editing performance.

Queue-based Self-Correction. In the context of SME, it is crucial to consider the inherent semantic associations among edited data. To manage dependency relationships in a long sequence of edits, we design a queue-based structure to store updated editing parameters following the first-in, first-out (FIFO) principle. Specifically, we insert the current editing parameters at the end of the queue and calculate the distance between the current parameters and those already in the queue. After sorting by distance, we update the original

parameters in the queue by comparing the gradient representation of the object entity with the relation representation of the current edit. For computational efficiency, we select only the top- K editing parameters for sequential updates. Finally, we remove the oldest parameters from the queue head to ensure the freshness of knowledge.

In our experiments, we evaluate QueueEDIT against model editing baselines on both single-turn and multi-turn editing, as well as on general NLP datasets. For SME, our method significantly surpasses baselines as the number of edits increases and even shows a slight advantage in single-turn editing. Regarding the analysis of general capabilities, our model shows better consistency than the original LLMs without any degradation in overall LLM performance.

2 Related Works on LLM Editing

Modifying Parameters. These approaches can be further divided into Locate-then-Edit and meta-learning-based methods. For Locate-then-Edit, ROME (Meng et al. 2022) and MEMIT (Chenmien Tan and Fu 2023) introduce a causal intervention framework to identify neuron activations and then update the knowledge data with low rank-based model editing to modify parameters. AlphaEdit (Fang et al. 2025) projects perturbations onto the null space of preserved knowledge prior to their application to the model parameters. For meta-learning methods, KnowledgeEditor (Cao, Aziz, and Titov 2021) and MEND (Mitchell et al. 2022a) employ distinct methodologies, converting edited knowledge and decomposed gradients of the LLM into weight offset modifications, respectively. MALMEN (Chenmien Tan

²The editing samples are sourced from knowledge graph (KG) triples $\langle \text{subject}, \text{relation}, \text{object} \rangle$ ($\langle s, r, o \rangle$).

and Fu 2023) advances this paradigm further by incorporating normal equations to optimize parameter integration for batch editing operations. DAFNet (Zhang et al. 2024) introduces intra-editing and inter-editing attention flows to update weighted representations at the sequence-level granularity. While these methods demonstrate efficacy in single or batch editing, the progressive accumulation of parameter modifications with an increasing number of edits may ultimately lead to editing degradation (Hu et al. 2024).

Adding Extra Parameters. This paradigm does not directly modify specific FFN layer parameters but adds training modules at corresponding positions to incorporate the edited data into the LLM. CaLiNet (Dong et al. 2022) and T-Patcher (Huang et al. 2023) achieve model editing by introducing additional neurons to the LLM for each piece of editing knowledge, thereby avoiding modifications to the original model parameters. GRACE (Hartvigsen et al. 2022) employs an adapter module that establishes a mapping between input queries and their corresponding knowledge representations. However, in an SME scenario, the persistent incorporation of new neurons to update the current edited data can overlook the correlations between different sequential editing data and increase the burden on model inference speed.

Retrieving Data. This approach enhances the model’s reasoning capabilities in a timely manner by continuously retrieving external data to supplement editing data without introducing additional parameters. Extending the GRACE framework, MELO (Yu et al. 2024) proposes a batch editing implementation leveraging LoRA technology (Hu et al. 2022). LTE (Jiang et al. 2024) fine-tunes the LLM to generate appropriate responses when provided with knowledge prefixed by editing cues, while leveraging the pre-trained backbone architecture for relevant content retrieval (Reimers and Gurevych 2019). However, the aforementioned methods, whether modifying parameters or retrieving external data, do not model the associations between sequential editing data in SME scenarios, resulting in logical errors between factual answers provided by LLMs.

3 Methodology

In this section, we introduce the basics of SME, including its definition, properties, and training losses. Then, we describe the main components of QueueEDIT, namely **Structural Mapping Editing** and **Queue-based Self-Correction**. The overall framework is illustrated in Figure 2.

3.1 Preliminaries of SME Task

Task Definition. Given an LLM f and an edit example (x_e, y_e) such that $f(x_e) \neq y_e$, a model editor (ME) outputs a post-edit model: $f' = \text{ME}(f, x_e, y_e)$. In SME, given a sequence of facts $\{(x_{e_1}, y_{e_1}), \dots, (x_{e_T}, y_{e_T})\}$ and an initial model f , a ME needs to conduct edits successively: $f_t = \text{ME}(f_{t-1}, x_{e_t}, y_{e_t})$ where $t = 1, \dots, T$ and $f_0 = f$. **Task Properties.** Every edit should satisfy basic properties: reliability, generality, and locality (Zhang et al. 2024).

Reliability: A reliable edit holds when the post-edit model f_t gives the target answer for the every cases (x_{e_τ}, y_{e_τ}) , $\tau \leq t$ to be edited. The reliability is measured as the average ac-

curacy on the edit cases:

$$\mathbb{E}_{(x_e, y_e) \sim \{(x_{e_\tau}, y_{e_\tau})\}_{\tau=1}^t} \mathbb{I} \left\{ \underset{y}{\operatorname{argmax}} f_t(y | x_e) = y_e \right\}. \quad (1)$$

Generality: The post-edit model f_t should also satisfy the relevant neighbors $N(x_{e_\tau}, y_{e_\tau})$, $\tau \leq t$. It is evaluated by the average accuracy of f_t on examples drawn uniformly from the relevant neighborhood:

$$\mathbb{E}_{(x_e, y_e) \sim \{(x_{e_\tau}, y_{e_\tau})\}_{\tau=1}^t} \mathbb{E}_{(x_g, y_g) \sim N(x_e, y_e)} G(x_g, y_g) \quad (2)$$

s.t. $G(x_g, y_g) = \mathbb{I} \left\{ \underset{y}{\operatorname{argmax}} f_t(y | x_g) = y_g \right\}.$

Locality: Editing should be local, which means the post-edit model f_t should not change the output of irrelevant examples in $O(x_{e_\tau}, y_{e_\tau})$, $\tau \leq t$. Hence, the locality is evaluated by the rate at which the post-edit model f_t ’s predictions are unchanged as the pre-edit model f :

$$\mathbb{E}_{(x_e, y_e) \sim \{(x_{e_\tau}, y_{e_\tau})\}_{\tau=1}^t} \mathbb{E}_{(x_l, y_l) \sim O(x_e, y_e)} L(x_l, y_l) \quad (3)$$

s.t. $L(x_l, y_l) = \mathbb{I} \{ f_t(y | x_l) = f(y | x_l) \}.$

Task Training. Let $(x_e^{(t)}, y_e^{(t)})$ be the reliability sample of the t -th fact, i.e., the editing sample itself. $(x_{g_j}^{(t)}, y_{g_j}^{(t)})$ and $N_g^{(t)}$ and $N_l^{(t)}$ are the corresponding sample numbers of the t -th fact. The total loss $\mathcal{L}_{ed}(f_T)$ is the sum of the following:

$$\mathcal{L}_{rel}(f_T) = \sum_{t=1}^T -\log f_T(y_e^{(t)} | x_e^{(t)}), \quad (4)$$

$$\mathcal{L}_{gen}(f_T) = \sum_{t=1}^T \sum_{j=1}^{N_g^{(t)}} -\log f_T(y_{g_j}^{(t)} | x_{g_j}^{(t)}), \quad (5)$$

$$\mathcal{L}_{loc}(f, f_T) = \sum_{t=1}^T \sum_{j=1}^{N_l^{(t)}} \text{KL}(f(x_{l_j}^{(t)}) || f_T(x_{l_j}^{(t)})). \quad (6)$$

3.2 Structural Mapping Editing

Our structural mapping editing approach maps the triplet structure to specific positions in the Transformer’s MLP layer, establishing semantic associations between the masked entity (i.e., the “Object”) and the “Subject” entity through independent “Relation” learning.

Locating the MLP Layer. Following Meng et al. (2022, 2023); Zhang et al. (2024), MLP layers in Transformers are selected for editing via causal tracing. These studies analyze all internal activations through three experimental runs in a Transformer language model to identify the layer with the largest indirect effect, denoted as l_0 . The layers act as two-layer key–value memories, where neurons of the first layer, $W_{fc}^{l_0}$, form a *key*, and neurons of the second layer, $W_{proj}^{l_0}$, represent the associated *value*.

Structural Triplet Editing. Editing a sample (x_e, y_e) constructed from a new triple $t^* = (s, r, o^*)$ in place of $t = (s, r, o)$ demonstrates a fine-grained understanding of the association-storage mechanisms. The parameters are derived via a closed-form solution (Meng et al. 2022, 2023):

$$W_{proj}^{l'_0} = W_{proj}^{l_0} + \Lambda(C^{-1}k_*)^T \quad (7)$$

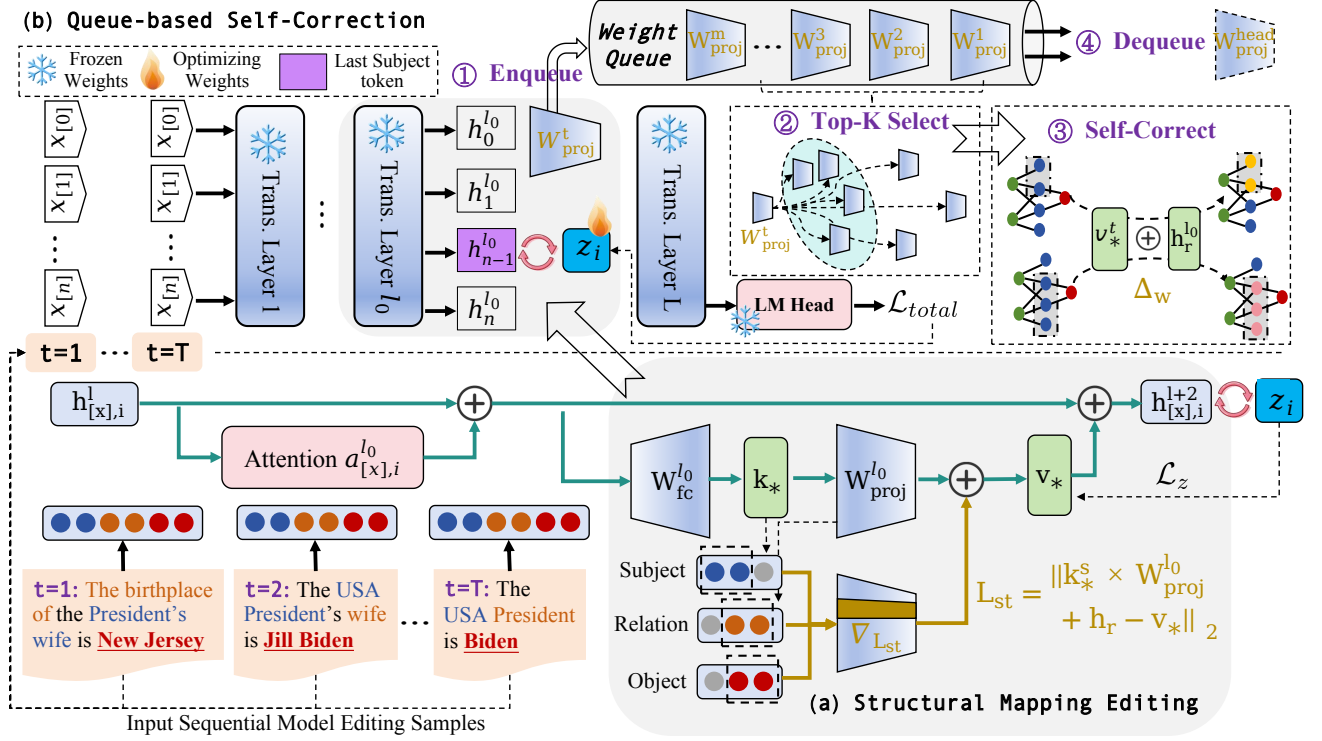


Figure 2: The QueueEDIT framework. (a) **Structural Mapping Editing** maps each triple (s, r, o) to dedicated positions (i.e., k_* , h_r , and v_*) within the FFN layer. (b) **Queue-based Self-Correction** stores the located parameters into a Weight Queue following the FIFO principle for subsequent semantic alignment, aiming to preserve the general capabilities of LLMs.

where $\Lambda = \frac{(v_* - W_{proj}^{l_0} k_*)}{(C^{-1} k_*^T k_*)}$ and $C = K \cdot K^T$ is a constant pre-computed using cached Wikipedia embeddings K from the editing triples.³ Here, k_* is obtained by forwarding an average over N sampled texts x formed by templates consisting of the subject s and relation r :

$$k_* = \frac{1}{N} \sum_{i=1}^N \sigma \left(W_{fc}^{l_0} \gamma(a_{[x],i}^{l_0} + h_{[x],i}^{(l_0-1)}) \right) \quad (8)$$

where $a_{[x],i}^{l_0}$ is the self-attention output at layer l_0 and $h_{[x],i}^{(l_0-1)}$ is the hidden input at layer $(l_0 - 1)$. γ is a normalization nonlinearity and σ is an activation function. From Eq. 8, we note that the relation r is mixed into the input x without separately modeling its structural semantics with the subject entity s and object entity o^* .

Triples $t^* = (s, r, o^*)$ can be represented by translation-based models (Bordes et al. 2013). These models imply that the semantics of object entities o^* can be approximated by subject entities s and relations r . Here, we inject structural semantics into the parameters to enhance knowledge memorization in MLP layers. Specifically, we first leverage the subject entity s and relation r to generate k_* via the MLP parameters W_{fc} using Eq. 8. The hidden representations are:

$$k_*^s = k_*[s_m : s_n], \quad k_*^r = k_*[r_m : r_n] \quad (9)$$

$$h_r = \sigma(k_*^r W_{proj}^{l_0} + b_r) \quad (10)$$

³We use backpropagation considering the object entity o^* to obtain v_* (Meng et al. 2022); please refer to Appendix C.

where s_m and s_n denote the subject token positions in the editing data, while r_m and r_n correspond to the relation positions. b_r is a bias term. k_*^s and h_r represent the subject and relation embeddings, respectively.

Next, we separate the relation r in triples and explicitly model it during the editing of the new knowledge triple (s, r, o^*) , rather than binding it with the subject entity s to transfer the contextual representation. The structural editing loss \mathcal{L}_{st} is defined as:

$$\mathcal{L}_{st} = \|k_*^s W_{proj}^{l_0} + h_r - v_*\|_2 \quad (11)$$

where the gradient of \mathcal{L}_{st} is used only to optimize $W_{proj}^{l_0}$, with all other parameters frozen.

By employing this translation-based loss, we constrain the transferred representation $(s+r) \rightarrow o^*$ to approximate the new knowledge o^* as closely as possible, while preserving the feature information of the old knowledge o stored in the located FFN layer $W_{proj}^{l_0}$.

3.3 Queue-Based Self-Correction

In previous SME methods (Cao, Aziz, and Titov 2021; Mitchell et al. 2022a; Zhang et al. 2024), $W_{proj}^{l_0}$ is repeatedly located for different triples, and knowledge is edited independently. Thus, the semantic influence among editing parameters is ignored, which leads to bias and adversely affects the general capabilities of LLMs (You et al. 2024). In QueueEDIT, we introduce a self-correction mechanism with a queue to update the located knowledge parameters in

each edit. Specifically, after each edited parameter is computed (denoted as \mathbf{W}_{proj}^t), we update the knowledge parameters in the queue according to the following steps to capture the semantic correlation of sequential edits and alleviate degradation in the general capabilities of LLMs.

Step 1: Enqueuing Located Parameters. We append the current edited knowledge parameter \mathbf{W}_{proj}^t to the end of the weight queue $Q = \langle W_{proj}^1, W_{proj}^2, \dots, W_{proj}^m \rangle$ ($m \geq 0$), where m denotes the number of located parameters currently in the queue Q . Thus, the updated queue order is $Q = \langle W_{proj}^1, W_{proj}^2, \dots, W_{proj}^m, \mathbf{W}_{proj}^t \rangle$.

Step 2: Selecting Top-K Parameters. Following the FIFO principle, the parameter bias at the front of the queue caused by the semantic gap with \mathbf{W}_{proj}^t has a greater impact on editing effectiveness (Gupta, Rao, and Anumanchipalli 2024; Gupta and Anumanchipalli 2024). Considering the trade-off between queue length and memory storage, we first identify the Top-K elements in the queue that need to be aligned. Specifically, we calculate the similarity in the editing parameter space between the current sample t and others using the Euclidean distance:

$$d_i = \|\mathbf{W}_{proj}^t - W_{proj}^i\|_2, \quad i = 1, 2, \dots, m \quad (12)$$

$$\mathcal{I}_{topK} = \{\sigma(1), \sigma(2), \dots, \sigma(K)\}, \quad K \leq m. \quad (13)$$

The function $\sigma(\cdot)$ denotes the sorting order such that $d_{\sigma(1)} \leq d_{\sigma(2)} \leq \dots \leq d_{\sigma(m)}$ and \mathcal{I}_{topK} is the index set of the Top-K parameters. Note that only when the similarity d_i is below a threshold η_{que} do we consider there to be a strong semantic correlation between the two parameter matrices, and thus align the semantic spaces between \mathbf{W}_{proj}^t and W_{proj}^i .

Step 3: Editing with Self-Correction. To iteratively update the dependency of previous data on the current editing sample in the SME task, we observe from Figure 1 that the parameters needing updates typically arise by linking the object o_*^t of the newly edited knowledge to the relation r^i of the previously edited knowledge. In general, it suffices to replace the object of the t -th sample with the subject of the i -th sample. Other parameters in the LLM and the queue Q remain frozen to preserve the general capabilities of the LLM. The effect of semantic superposition is analogous to prior work on embedding translation operations (Bordes et al. 2013; Lin et al. 2015).

Concretely, we leverage the Top-K located parameters $\{W_{proj}^1, W_{proj}^2, \dots, W_{proj}^K\}$ and align them semantically with the current edited knowledge \mathbf{W}_{proj}^t . The update rule for previously semantically dependent editing samples is:

$$\Delta_W = v_*^t \oplus h_r^i, \quad i \in \mathcal{I}_{topK} \quad (14)$$

$$W_{proj}^{i'} = \sigma(W_{proj}^i \parallel \Delta_W + b') \quad (15)$$

where \oplus denotes element-wise addition and \parallel denotes concatenation. $W_{proj}^{i'}$ is the self-corrected editing parameter in the queue that will be aligned back into the LLM. Due to the limited length of the queue, the oldest knowledge parameter is dequeued in the next step after each self-correction.

Step 4: Dequeuing Located Parameters. According to the FIFO principle, the edited triple at the head of the queue, W_{proj}^{head} , is the farthest from the current editing sample W_{proj}^t

and thus has the smallest semantic correlation. We use Eq. 12 to calculate the similarity d_{head} between them to determine whether to dequeue:

$$\text{Dequeue}(Q) \triangleq \begin{cases} \langle Q \setminus \{W_{proj}^{head}\} \rangle & d_{head} < \eta_{deq}, \\ Q & \text{otherwise.} \end{cases} \quad (16)$$

where η_{deq} is the dequeue threshold hyperparameter.

3.4 Model Training

To satisfy the three desired properties for SME (reliability, generality, and locality), we adopt the same loss formulations with respect to T SME facts as in previous model editing works (Meng et al. 2023; Zhang et al. 2024). The total loss is the sum of the structural editing loss and the typical model editing losses used in prior studies, expressed as: $\mathcal{L}_{total} = \alpha_1 \cdot \mathcal{L}_{ed}(f_T) + \alpha_2 \cdot \mathcal{L}_{st}(f_T)$, where α_i are coefficients satisfying $\sum_{i=1}^2 \alpha_i = 1$.

4 Experiments

Due to space limitations, the descriptions of datasets, baselines, and implementations are provided in Appendix A.

4.1 Main Results

Model Editing Results. We evaluate QueueEDIT on three benchmarks and compare performance with 1000 edits⁴. Table 1 shows the overall performance. We observe the following: (1) Methods based on modifying parameters show a sharp decrease in performance as the number of edits increases. We hypothesize that meta-learning methods do not account for the sequential modeling of facts. The weight update training of located neurons in meta networks is carried out separately with a small amount of data, so these methods cannot capture the relationships between sequential editing data. Although locate-then-edit models have less performance degradation with increasing edits compared to meta-learning-based models, we find they are more sensitive to the backbone. When using LLAMA3 as the backbone, the accuracy of such models is nearly zero, especially in long editing scenarios (e.g., 1000 edits). KN (Dai et al. 2022) achieves editing by performing excessive activation when dealing with multiple facts. (2) Methods that add extra parameters do not modify the original parameters inside the model, but add new neurons or modules at the located positions, which can partially capture the inherent connections among sequences. However, as the number of edits increases, the model’s performance gradually decreases regardless of the backbone. (3) Retrieve-data methods freeze the original parameters of LLMs and do not add additional parameters; retrieving external data only for the current editing sample cannot effectively correlate or model previous edits. (4) QueueEDIT modifies only parameters for the current edit, while using a queue structure to self-correct correlations between previously edited data. Therefore, the model not only achieves strong editing results but also maintains good stability during long sequence editing.

⁴The results for 1, 10, and 100 edits are shown in Appendix B.1.

Backbone	Editor	ZSRE				CounterFact				RIPE			
		Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.
GPT-J (6B)	FT	4.3	3.0	0.1	2.5(± 0.1)	12.9	5.1	1.1	6.4(± 0.1)	3.1	0.9	0.8	1.6(± 0.0)
	KN	0.8	0.0	2.2	1.0(± 0.0)	0.1	0.4	1.0	0.5(± 0.0)	0.0	0.0	0.0	0.0(± 0.0)
	ROME	57.2	53.9	29.9	47.0(± 1.1)	0.2	0.2	0.0	0.1(± 0.0)	47.5	16.9	13.4	26.0(± 0.5)
	MEMIT	56.8	54.6	54.9	55.4(± 1.3)	42.3	36.4	30.7	49.8(± 1.3)	0.0	0.0	0.0	0.0(± 0.0)
	KE	0.0	0.0	1.1	0.4(± 0.0)	0.0	0.0	0.1	0.0(± 0.0)	0.0	0.0	0.2	0.1(± 0.0)
	MEND	0.0	0.0	0.0	0.0(± 0.0)	0.0	0.0	0.0	0.0(± 0.0)	0.2	0.1	0.1	0.1(± 0.0)
	MALMEN	43.0	35.1	39.3	39.1(± 0.4)	15.0	12.4	25.1	17.5(± 0.4)	31.1	19.1	35.3	28.5(± 0.6)
	DAFNet	60.0	57.6	88.0	68.5(± 1.9)	53.1	38.1	82.3	57.8(± 1.2)	48.3	31.3	57.3	45.6(± 1.2)
	AlphaEdit	40.2	35.2	62.1	45.8(± 1.3)	37.5	21.4	59.5	39.5(± 1.5)	31.6	19.8	43.2	31.5(± 1.1)
	TP	45.7	40.4	10.5	32.2(± 0.8)	47.3	17.0	1.4	21.9(± 0.7)	48.1	29.1	15.2	30.8(± 0.6)
	GRACE	56.2	51.3	28.4	45.3(± 1.2)	0.3	0.4	0.1	0.3(± 0.1)	46.7	16.3	13.8	25.6(± 0.7)
	MELO	48.7	42.6	68.8	53.4(± 1.3)	41.6	28.3	65.1	45.0(± 0.5)	34.2	23.6	48.3	35.4(± 1.1)
	LTE	53.2	46.5	73.5	57.7(± 1.4)	46.6	32.5	73.1	50.7(± 1.0)	41.2	28.7	53.0	41.0(± 0.6)
	QueueEDIT	64.5	60.1	92.6	72.4 (± 1.1)	64.8	43.2	88.4	65.5 (± 1.1)	51.7	37.9	62.2	50.6 (± 0.7)
LLAMA3 (8B)	FT	8.4	7.2	5.1	6.9(± 0.1)	2.0	0.6	2.2	1.6(± 0.0)	3.2	1.5	2.7	2.5(± 0.0)
	KN	0.5	0.8	0.5	0.6(± 0.1)	0.9	0.2	0.1	0.4(± 0.1)	0.6	0.4	0.5	0.5(± 0.1)
	ROME	2.1	2.0	1.1	1.7(± 0.1)	0.7	0.6	0.6	0.6(± 0.1)	0.5	0.5	0.5	0.5(± 0.1)
	MEMIT	0.7	0.7	0.6	0.7(± 0.1)	0.6	0.6	1.5	0.9(± 0.1)	0.1	0.5	0.6	0.4(± 0.1)
	KE	0.3	0.8	0.6	0.5(± 0.1)	0.5	0.5	0.8	0.6(± 0.1)	0.0	0.2	0.1	0.1(± 0.1)
	MEND	0.8	0.1	0.3	0.4(± 0.1)	0.3	0.8	0.4	0.5(± 0.1)	0.0	0.2	0.6	0.3(± 0.1)
	MALMEN	32.9	29.4	29.0	30.4(± 0.6)	16.7	17.3	23.4	19.1(± 0.3)	43.2	39.3	39.4	40.6(± 0.9)
	DAFNet	51.4	49.5	94.5	65.1(± 1.3)	51.3	36.7	77.8	55.3(± 1.6)	45.0	35.2	86.7	55.6(± 0.9)
	AlphaEdit	34.2	28.6	71.8	44.9(± 1.1)	34.6	23.1	65.0	40.9(± 1.3)	29.1	22.4	71.1	40.9(± 1.1)
	TP	48.2	45.0	5.1	32.8(± 0.6)	65.6	33.4	12.3	37.1(± 0.9)	43.2	27.7	10.8	27.2(± 0.6)
	GRACE	2.0	2.1	1.3	1.8(± 0.1)	0.6	0.7	0.6	0.6(± 0.1)	0.3	0.2	0.5	0.3(± 0.1)
	MELO	39.2	32.5	75.3	49.0(± 1.4)	40.3	27.1	70.2	45.9(± 1.3)	34.5	26.2	75.8	45.5(± 1.6)
	LTE	43.7	40.6	82.3	55.5(± 1.0)	44.5	31.7	73.5	49.9(± 1.4)	42.0	32.6	81.5	52.0(± 1.2)
	QueueEDIT	56.1	55.0	96.2	69.1 (± 1.3)	60.5	44.7	80.1	61.8 (± 0.7)	49.1	44.4	90.0	61.2 (± 0.8)

Table 1: Overall results of QueueEDIT under 1000 edits. “Rel.”, “Gen.”, and “Loc.” represent the editing metrics, respectively. Due to space limitations, the results for 1, 10, and 100 edits are provided in Appendix B.1.

General Capabilities of LLMs. We further investigate the extent to which these editors influence the general capabilities of LLMs during SME. Figure 3 shows the averaged accuracy results for LLaMA3 (8B) after 10, 100, 500, and 1000 edits over public LLM benchmarks. The benchmark datasets typically consist of QA tasks similar to the editing samples, thereby alleviating bias due to differences in data format between training and testing. It is observed that previous SME methods harm the general capabilities of LLMs as the number of edits increases. Grace (Hartvigsen et al. 2022) leverages extra datasets and adapters to preserve general performance. Retrieval-based methods perform relatively better than other baselines. We conjecture that the retrieved external data may be mixed with diverse types of knowledge, which helps alleviate the loss of model generality. In contrast, QueueEDIT performs self-correction only on the parameters corresponding to previously associated edited data during the queue update process, while freezing other parameters in both the queue and LLMs. Therefore, our model better generalizes on other open-domain questions.

4.2 Ablation Study

We conduct an ablation study using LLaMA3 (8B), with averaged results presented in Table 3. The structural mapping editing is replaced with the original editing representation k_* , which mixes the subject and relation (Meng et al. 2022).

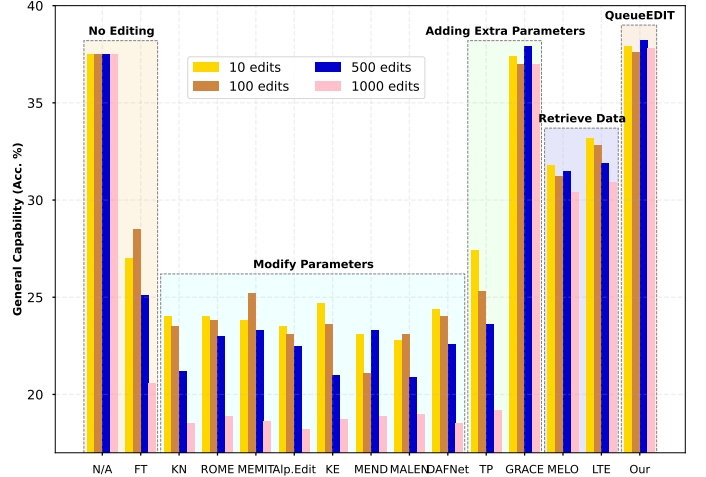


Figure 3: The “improvement/degeneration” of general capability after performing the SME task across various editing paradigms. “N/A” indicates the original results of the LLMs.

When we remove the queue-based self-correction, the overall system degrades to a basic locate-the-editing paradigm equipped with the structural editing loss. In addition, we evaluate the effect of selecting parameters by removing the Top-K calculation and instead using random selection.

We observe that without queue-based learning, perfor-

Backbone	QL	Mem. (GB)	ZSRE				CounterFact				RIPE			
			Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.
LLAMA3 (8B)	10%	12.5	49.4	50.4	92.0	63.9(± 0.5)	47.5	38.8	70.3	52.2(± 0.3)	45.0	41.0	80.1	55.4(± 0.5)
	30%	21.8	56.1	55.0	96.2	69.1 (± 1.3)	60.5	44.7	80.1	61.8 (± 0.7)	49.1	44.4	90.0	61.2 (± 0.8)
	50%	32.3	49.0	51.8	92.5	64.4(± 0.5)	52.4	38.2	73.2	54.6(± 0.4)	45.6	39.7	83.5	56.3(± 0.2)
	Memory Consumption of Baselines													
	FT	KN	ROME	MEMIT	KE	MEND	MALMEN	DAFNet	AlphaEdit	TP	Grace	MELO	LTE	-
	60.2	31.4	18.3	25.6	13.9	16.2	13.7	30.5	26.7	14.8	47.1	36.5	28.3	-

Table 2: Results of QueueEDIT with different queue lengths in 1000 edits. “QL” indicates the queue length.

Modules	100 edits			1000 edits			Avg.
	Rel.	Gen.	Loc.	Rel.	Gen.	Loc.	
Ours	77.1	56.5	91.1	55.2	54.7	88.8	70.6
w/o \mathcal{L}_{st}	72.4	51.8	84.9	48.3	49.9	82.3	64.9
w/o Queue	59.0	45.2	73.8	40.4	39.5	69.7	54.6
w/o Top-K	73.5	53.6	88.0	51.3	50.5	86.1	67.2

Table 3: Ablation study of QueueEDIT.

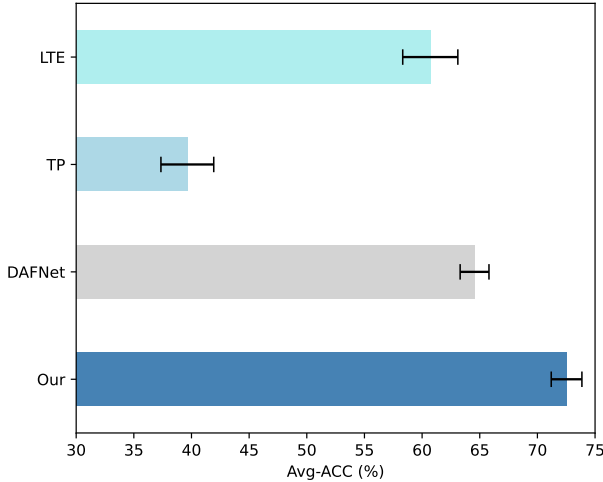


Figure 4: Results using Qwen2.5-14B as the backbone.

mance decreases significantly due to the lack of alignment among sequential editing samples in the editing parameters. The decrease observed when the structural mapping loss is removed indicates that editing knowledge through structural semantics is more effective than directly mixing triplet data together, as in previous works (Meng et al. 2022, 2023). After removing the Top-K selection mechanism, the decrease in model performance suggests that randomly selecting semantically unrelated triple parameters for alignment disrupts the consistency of parameter learning and leads to reduced model editing capability.

4.3 Detailed Analysis

Queue Length. We analyze memory usage and performance changes as the queue length increases. Other methods, especially those with additional parameters, require extra memory to train the knowledge adapter module. We set the queue length to 10%, 30%, and 50% of 1000 edits to evaluate editing performance and memory consumption. For memory consumption, we compare the number of parameters used

by the additional editor regardless of the frozen LLMs. As shown in Table 2, although QueueEDIT consumes slightly more memory compared to baseline methods, its performance improves significantly as the number of edits increases. Additionally, we find that longer queue lengths lead to less consistent editing performance, possibly due to the introduction of more irrelevant knowledge parameters and semantic noise.

Qualitative Analysis of Queue-Based Self-Correction. We present case studies demonstrating the queue-based self-correction of relevant knowledge within QueueEDIT. Due to space limitations, please refer to Appendix B.2 and B.3.

Larger LLMs as Backbones. The mainstream LLM backbones used in model editing are GPT-J (6B) and LLaMA3 (8B) (Mitchell et al. 2022b; Madaan et al. 2022; Zheng et al. 2023; Zhang et al. 2024; Fang et al. 2025). We further test our model’s effectiveness using a larger backbone. Due to limited GPU resources, we select the larger-scale Qwen2.5-14B model (Qwen Team 2024), a state-of-the-art LLM, for our experiments. The experimental setup includes several competitive editing paradigms (i.e., DAFNet, TP, and LTE) with 1000 sequential edits. We report average results on three editing properties using F1 (%).

From Figure 4, we observe that: (1) Utilizing a larger-scale backbone model for SME further enhances editing performance. This improvement is likely due to the increased capacity for internal parameterized knowledge storage in larger models compared to smaller LLMs, allowing more effective collaborative modeling via both internal and external knowledge sources. (2) With the advantage of a larger backbone, our QueueEDIT model demonstrates significant performance improvements over baselines.

5 Conclusion

In this paper, we propose QueueEDIT, a novel queue-based self-correction framework designed for SME in LLMs. Our approach introduces a structural mapping editing loss to effectively associate knowledge triplets with knowledge-sensitive neurons within Transformer layers. By storing and dynamically aligning editing parameters in a queue, QueueEDIT captures long-sequence dependencies and selectively updates relevant parameters, thereby mitigating the negative impact of parameter bias on the general capabilities of LLMs. Extensive experiments demonstrate that QueueEDIT significantly outperforms strong baselines across diverse SME scenarios, and effectively preserves the general language understanding abilities of LLMs throughout the editing process.

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A Implementation Details

A.1 Data

Training Data. Following (Yao et al. 2023), we use the ZSRE training data containing 162,555 entries, the CF training data containing 10,000 entries, and the enhanced dataset DAFSet (Zhang et al. 2024) to train meta-learning-based models, including KE (Cao, Aziz, and Titov 2021) and MEND (Mitchell et al. 2022a).

Evaluation Data. We utilize three widely used datasets for evaluation. **ZSRE** (Levy et al. 2017) employs BART (Lewis et al. 2020) to answer questions followed by manual filtering, resulting in each instance containing an editing sample, a rephrased counterpart, and an irrelevant sample corresponding to reliability, generality, and locality, respectively. Inspired by (Yao et al. 2023), we split the dataset into a training set and a testing set, with 162,555 and 19,009 entries. In **CF** (Meng et al. 2022), all the facts to be edited are false, thus increasing the difficulty of editing tasks. Similar to ZSRE, each data point contains an editing sample, a rephrased sample, and an irrelevant sample. Following Yao et al. (2023), both the training and testing sets comprise 10,000 entries. **RIPE** (Cohen et al. 2023) intricately subdivides generality and locality into multiple components. Similar to CF, it involves editing false facts and is characterized by detailed evaluation. After pre-processing, a total of 4,388 entries are collected.

General Capability Datasets. We evaluate the general capability of various methods using these four authoritative datasets: CSQA (Saha et al. 2018), MMLU (Hendrycks et al. 2021), ANLI (Nie et al. 2020), and SQUAD-2 (Rajpurkar et al. 2016). CSQA contains 200K dialogs with 1.6M turns. MMLU contains 15,908 questions. ANLI contains 3,200 test samples, and SQUAD-2 collects 8,862 questions.

Backbone	# Editing	Editor	ZSRE				CounterFact				RIPE			
			Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.
LLAMA3 (8B)	1	FT	53.3	53.7	92.6	66.5(± 0.3)	34.6	25.9	50.3	36.9(± 0.5)	49.7	34.2	71.5	51.8(± 0.5)
		KN	20.7	21.3	52.9	31.6(± 0.1)	12.8	9.7	68.4	30.3(± 0.4)	22.3	15.9	55.9	31.4(± 0.5)
		ROME	54.0	52.1	94.5	66.9(± 0.7)	41.6	22.3	92.3	52.1(± 0.8)	48.8	27.6	43.0	39.8(± 0.9)
		MEMIT	50.2	49.9	92.4	64.2(± 0.5)	45.9	29.8	93.4	56.4(± 0.4)	58.9	30.1	39.2	42.7(± 0.3)
		KE	13.4	9.1	91.1	37.9(± 0.2)	8.5	3.4	90.8	34.2(± 0.4)	10.4	4.9	43.3	19.5(± 0.2)
		MEND	74.3	70.8	66.6	70.6(± 0.5)	81.6	67.7	77.6	75.6(± 0.3)	66.9	29.9	30.2	42.3(± 0.5)
		MALMEN	66.9	68.3	44.2	59.8(± 0.5)	52.9	42.8	37.1	44.3(± 0.6)	52.0	34.3	21.0	35.8(± 0.9)
		DAFNet	97.9	97.8	95.4	97.0(± 1.5)	92.5	87.2	94.8	91.5(± 0.8)	98.2	66.9	72.7	79.3(± 0.7)
		AlphaEdit	98.6	98.6	95.8	97.7(± 1.2)	93.3	88.6	95.7	92.5(± 0.9)	97.9	67.6	73.5	79.7(± 0.5)
		TP	86.9	84.5	86.9	86.1(± 1.4)	91.9	69.1	39.5	66.8(± 0.3)	77.5	55.6	51.8	61.6(± 0.5)
		GRACE	52.8	51.3	96.2	66.8(± 0.9)	45.1	29.0	93.9	56.0(± 0.5)	57.2	31.1	41.6	43.3(± 0.2)
		MELO	97.3	96.5	92.2	95.3(± 1.1)	91.4	84.9	92.6	89.6(± 1.0)	93.3	64.0	68.8	75.4(± 0.5)
		LTE	97.7	96.9	93.5	96.0(± 1.1)	92.2	85.8	93.4	90.5(± 0.7)	94.6	65.4	70.1	76.7(± 1.3)
		QueueEDIT	98.6	99.6	97.0	98.4 (± 0.5)	93.9	88.4	96.1	92.8 (± 0.6)	98.2	68.8	76.2	81.1 (± 0.9)

Table 4: The overall results in single-turn editing.

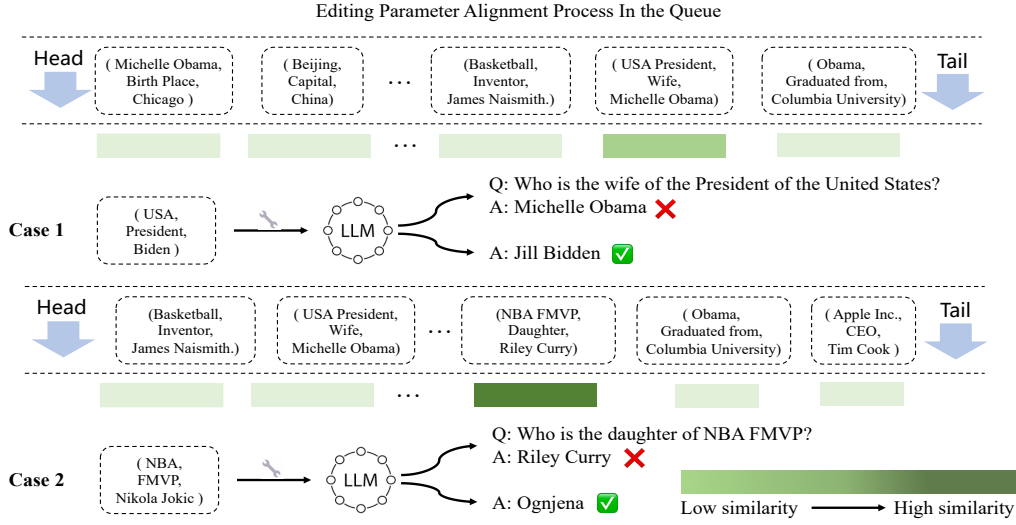


Figure 5: Qualitative analysis of queue-based self-correction in two case studies.

A.2 Baselines

Modify Parameters: (1) KN (Dai et al. 2022) uses an integral gradient-based method to locate neurons in the FFN, achieving editing by amplifying the activation of the located neurons. (2) ROME (Meng et al. 2022) first uses causal mediation analysis to locate the layer that has the greatest impact on the editing sample. They propose ROME to modify the FFN weights of the located layer. (3) MEMIT (Meng et al. 2023) expands the editing scope to multiple layers based on ROME, thereby improving editing performance and supporting batch editing. (4) AlphaEdit (Fang et al. 2025) maps perturbations into the null space of retained knowledge prior to their integration into the parameters. For the latter, (1) KE (Cao, Aziz, and Titov 2021) trains a bidirectional LSTM auxiliary network to predict weight updates of the editing samples. (2) MEND (Mitchell et al. 2022a) trains an MLP to transform the low-rank decomposition of the gradients of the model to be edited with respect to the editing samples and updates the model with the transformed gradients to achieve editing. (3) MALMEN (Chenmian Tan and Fu 2023) accommodates editing of multiple

facts with limited memory budgets by separating the computation on the hyper-network and LM, enabling an arbitrary batch size on both neural networks. (4) DAFNet (Zhang et al. 2024) proposes intra-inter editing attention to enhance the sequential editing of samples. In addition, the DAFSet dataset is also proposed to train the meta-learning-based editors. For baseline implementation, we use the same settings in EasyEdit (Wang et al. 2023) for training and evaluation.

Adding Extra Parameters: T-Patcher (Huang et al. 2023) attaches and trains additional neurons in the FFN of the last layer of the model to be edited. GRACE (Hartvigsen et al. 2022) proposes General Retrieval Adapters for Continuous Editing (GRACE), which maintain a dictionary-like structure to construct new mappings for potential representations that need to be modified.

Retrieve Data: MELO (Yu et al. 2024) introduces an implementation for batch editing that utilizes LoRA technology (Hu et al. 2022). Meanwhile, LTE (Jiang et al. 2024) employs fine-tuning of the LLMs to produce contextually appropriate responses when presented with knowledge preceded by specific editing cues, while simultaneously exploiting the pre-trained backbone architecture for the retrieval of

relevant content (Reimers and Gurevych 2019).

A.3 Experimental Settings

We use GPT-J⁵ and LLaMA3 (Dubey et al. 2024) as our backbones for editing. The queue similarity thresholds η_{que} and η_{deq} are set to 0.5. The hyperparameter K is set to 50 due to limitations of machine resources. Regarding the selection of editing weights, we use settings consistent with MEND (Mitchell et al. 2022a) and KE (Cao, Aziz, and Titov 2021): both GPT-J and LLaMA3 use the FFN weights of the last three layers of the model.

The upper limit for the number of sequential editing models is 1000, i.e., $T_{max} = 1000$. When the number of sequential editing models reaches the maximum value, we perform an additional 20,000 iterations before stopping. We store checkpoints every 1000 iterations, and the checkpoint with the lowest loss is selected for evaluation. The learning rate η is set to $1e-6$. The training process takes 2 days on 8 NVIDIA A800 GPUs. These experiments are presented as averages from 5 random runs with different random seeds and the same hyperparameters.

B Editing Results

B.1 Results for Other Editing Quantities

The experimental results for 1, 10, and 100 edits are shown in Tables 4 and 5, respectively. These results are consistent with our main experiments, further demonstrating the effectiveness of our approach.

B.2 Case Study

We further conduct a detailed analysis of the queue memory by selecting parameter blocks updated from the queue. Specifically, we perform a semantic similarity analysis on the top-3 most relevant triples in sequential editing knowledge from the ZSRE dataset.

- Case 1: Q: Who was the designer of Lahti Town Hall?
A: Eliel Saarinen.
Top-1: Q: By which person was Lahti Town Hall designed? A: Eliel Saarinen.
Top-2: Q: When was Lahti Town Hall designed? A: 1911.
Top-3: Q: Where did the dark bricks come from for the materials used in Lahti Town Hall? A: Sweden.
- Case 2: Q: Which was the manufacturer of USS Leedstown (APA-56)? A: Bethlehem Steel.
Top-1: Q: Which corporation created USS Leedstown (APA-56)? A: Bethlehem Steel.
Top-2: Q: When was USS Leedstown (APA-56) scrapped? A: 1970.
Top-3: Q: How long did USS Leedstown (APA-56) serve? A: 1943-1946.
- Case 3: Q: In what language are the Garowe Principles written? A: Somali.
Top-1: Q: In which language is the Garowe Principles monthly football magazine reported? A: Somali.

Top-2: Q: Where were the Garowe Principles signed?
A: Garowe.

Top-3: Q: Which representatives voted on The Garowe Principles? A: Transitional Federal Government.

We observe that: (1) The MLP parameters requiring editing alignment for Top-1 are likely semantically consistent with the current edited data. (2) The semantic alignment parameters for the remaining data (Top-2 and Top-3) are generally consistent with the subject entities or relations. In summary, the top- K data aligned with the current editing knowledge in the queue is semantically consistent at the level of important entities or relations.

B.3 Queue-Based Self-Correction Cases

To analyze how our QueueEDIT method improves the effectiveness of SME, we visualize samples from the test dataset. As shown in Figure 5, when asked the question, “Who is the wife of the President of the United States?”, the strongest baseline model incorrectly answers “Michelle Obama”. In contrast, our QueueEDIT model calculates the semantic similarity among all edited knowledge parameters in the queue and identifies that the knowledge fact “(USA President, Wife, Michelle Obama)” requires alignment with the current editing fact “(USA President, Biden)” due to high similarity.

In Case 2, our QueueEDIT model correctly recognizes the fact “(NBA FMVP, Daughter, Riley Curry)” as having the highest similarity and requiring alignment, since the NBA FMVP recipient is “Nikola Jokic”. This demonstrates that our queue-based dynamic alignment mechanism can better model relationships between sequential editing data and promptly update correlations among facts.

C Detailed Calculation of v_*

ROME (Meng et al. 2022) aims to choose a token vector value v_* that encodes the new relation (r, o^*) as a property of s . They set $v_* = \arg \min_z \mathcal{L}(z)$, where z is the hidden representation of o^* , and the objective $\mathcal{L}(z)$ is defined as:

$$\mathcal{L}_z = \underbrace{\frac{1}{N} \sum_{j=1}^N -\log \mathbb{P}_G(m_i^{(t^*)} := z) [o^* | x_j + p]}_{\text{(a) Maximizing } o^* \text{ probability}} + \underbrace{D_{KL} \left(\mathbb{P}_{G(m_i^{(t^*)} := z)} [x | p'] \parallel \mathbb{P}_G [x | p'] \right)}_{\text{(b) Controlling semantic drift}}, \quad (17)$$

where the first term searches for a vector z such that, when it replaces the MLP’s output at the i -th token (the subject’s final position, denoted as $G(m_i^{(t^*)} := z)$), the network predicts the desired object o^* in response to the factual prompt p . The second term reduces the KL divergence between predictions for the prompt p' (of the form “{subject} is a”) and those of the original model, ensuring the model retains its grasp of the subject’s core meaning.

⁵<https://huggingface.co/EleutherAI/gpt-j-6b>

Backbone	# Editing	Editor	ZSRE				CounterFact				RIPE			
			Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.	Rel.	Gen.	Loc.	Avg.
GPT-J (6B)	10	FT	10.3	10.8	0.3	7.1(± 0.1)	56.2	24.2	2.1	27.5(± 0.5)	7.8	4.3	1.4	4.5(± 0.1)
		KN	1.0	1.1	1.9	1.3(± 0.0)	1.2	0.7	2.3	1.4(± 0.0)	0.1	0.3	0.2	0.2(± 0.0)
		ROME	81.1	78.8	94.6	84.8(± 1.7)	95.9	59.4	90.0	81.8(± 1.9)	98.2	41.9	39.1	59.7(± 0.8)
		MEMIT	82.1	76.0	94.7	84.2(± 2.0)	96.0	38.1	95.5	76.5(± 2.5)	98.5	37.7	47.3	61.2(± 1.2)
		KE	0.0	0.0	0.7	0.3(± 0.0)	0.0	0.0	0.2	0.1(± 0.0)	0.0	0.0	0.1	0.0(± 0.0)
		MEND	0.4	0.4	0.5	0.4(± 0.0)	0.6	0.2	0.2	0.3(± 0.0)	0.0	0.0	0.0	0.0(± 0.0)
		MALMEN	99.1	95.3	92.8	95.8(± 1.6)	90.0	32.9	77.1	66.7(± 2.2)	89.7	52.1	51.3	64.4(± 1.8)
		DAFNET	99.6	97.6	94.8	97.3(± 1.5)	96.2	65.8	85.2	82.4(± 1.6)	98.7	57.6	57.8	71.4(± 1.6)
		AlphaEdit	99.9	98.1	95.2	97.7(± 1.1)	96.8	66.5	86.8	83.4(± 1.0)	98.9	58.2	59.0	72.0(± 1.4)
		TP	85.2	78.3	77.2	80.2(± 1.2)	96.0	54.3	3.6	51.3(± 1.2)	80.8	56.7	32.4	56.6(± 1.7)
		GRACE	81.8	78.4	94.5	84.9(± 1.6)	95.2	60.3	91.2	82.2(± 1.6)	98.0	40.9	38.7	59.2(± 0.4)
	100	MELO	98.2	96.5	92.8	95.8(± 0.9)	95.2	63.6	84.5	81.1(± 2.1)	96.6	51.9	55.7	68.1(± 0.8)
		LTE	98.7	96.1	93.2	96.0(± 1.3)	94.3	60.6	82.3	79.1(± 1.0)	94.5	48.4	53.6	65.5(± 0.9)
		QueueEDIT	99.9	98.7	95.9	98.2 (± 0.6)	97.5	68.2	89.4	85.0 (± 0.8)	99.8	61.3	61.4	74.2 (± 1.1)
		FT	2.2	1.9	0.3	1.4(± 0.0)	35.9	10.8	1.6	16.1(± 0.3)	5.7	1.6	0.1	2.5(± 0.1)
		KN	0.6	0.4	0.8	0.6(± 0.0)	0.2	0.5	0.8	0.5(± 0.0)	0.0	0.0	0.0	0.0(± 0.0)
		ROME	77.4	75.6	85.0	79.3(± 2.2)	78.8	38.4	52.2	56.5(± 1.0)	95.7	36.0	32.2	54.6(± 1.0)
		MEMIT	77.9	74.1	90.2	80.7(± 2.5)	94.1	40.2	85.1	73.1(± 1.3)	86.6	33.3	33.5	51.1(± 1.3)
		KE	0.0	0.0	0.7	0.2(± 0.0)	0.0	0.0	0.1	0.0(± 0.0)	0.0	0.0	0.0	0.0(± 0.0)
		MEND	0.2	0.1	0.0	0.1(± 0.0)	0.2	0.2	0.0	0.1(± 0.0)	0.0	0.0	0.1	0.0(± 0.0)
		MALMEN	50.6	40.7	59.3	50.2(± 0.8)	29.7	31.8	68.0	43.2(± 0.4)	39.9	27.8	53.2	40.3(± 0.8)
		DAFNET	89.5	76.5	90.2	85.4(± 1.6)	81.8	40.3	87.3	69.8(± 1.5)	78.5	38.9	64.4	60.6(± 1.5)
		AlphaEdit	80.2	67.1	82.5	76.6(± 0.8)	70.7	35.9	74.8	60.5(± 1.2)	71.9	36.3	59.2	55.8(± 1.3)
	100	TP	68.5	59.3	52.8	60.2(± 1.3)	76.0	31.9	2.2	36.7(± 0.8)	64.2	36.4	23.7	41.4(± 1.0)
		GRACE	77.8	74.6	85.9	79.4(± 2.0)	76.3	39.2	51.6	55.7(± 0.8)	94.8	36.7	31.5	54.3(± 0.8)
		MELO	78.4	65.3	82.9	75.5(± 0.8)	79.4	41.7	79.9	67.0(± 1.2)	74.6	30.1	52.3	52.3(± 0.7)
		LTE	81.5	70.5	83.4	78.5(± 1.7)	78.3	38.7	80.6	65.9(± 1.0)	75.1	35.9	62.7	57.9(± 0.8)
		QueueEDIT	93.5	78.6	94.2	88.8 (± 1.3)	92.6	52.3	90.1	78.3 (± 0.9)	94.9	43.8	68.7	69.1 (± 0.9)
LLAMA3 (8B)	10	FT	38.7	38.1	58.5	45.1(± 0.9)	19.7	14.2	23.0	19.0(± 0.2)	31.0	22.5	28.7	27.4(± 0.7)
		KN	0.9	0.9	1.4	1.1(± 0.1)	1.2	1.1	4.9	2.4(± 0.1)	0.9	0.9	0.8	0.9(± 0.1)
		ROME	41.6	40.3	93.6	58.5(± 1.4)	39.1	25.6	84.3	49.7(± 1.0)	33.9	21.0	30.2	28.4(± 0.6)
		MEMIT	24.8	24.7	51.8	33.8(± 0.9)	19.1	15.9	63.5	32.8(± 0.7)	18.9	14.2	10.8	14.6(± 0.3)
		KE	1.2	1.2	1.9	1.4(± 0.1)	0.7	0.7	0.8	0.7(± 0.1)	0.8	0.9	1.7	1.1(± 0.1)
		MEND	1.0	1.0	3.8	1.9(± 0.1)	0.7	0.7	0.8	0.7(± 0.1)	1.0	1.0	2.1	1.4(± 0.1)
		MALMEN	96.7	89.0	93.3	93.0(± 1.8)	80.0	46.5	36.9	54.5(± 1.1)	85.2	48.2	71.6	68.3(± 2.3)
		DAFNET	97.7	92.7	94.0	94.8(± 1.2)	87.8	60.3	86.5	78.2(± 1.4)	89.3	57.1	83.9	76.8(± 1.9)
		AlphaEdit	98.2	92.3	94.5	95.0(± 1.1)	88.1	61.4	86.7	78.7(± 0.8)	90.1	58.6	84.5	77.7(± 1.2)
		TP	57.8	53.1	37.4	49.4(± 1.1)	86.4	59.3	22.2	56.0(± 0.9)	63.9	42.0	31.1	45.7(± 0.8)
	100	GRACE	43.0	40.4	93.1	58.8(± 1.5)	38.6	25.2	83.3	49.0(± 0.8)	31.9	21.5	29.8	27.7(± 0.5)
		MELO	97.5	93.3	94.2	95.0(± 1.1)	86.2	57.8	83.5	75.8(± 1.7)	88.0	54.4	79.9	74.1(± 1.2)
		LTE	96.9	93.5	93.2	94.5(± 1.6)	88.5	58.5	87.1	78.0(± 1.6)	87.2	55.7	80.2	74.4(± 1.1)
		QueueEDIT	99.2	94.6	96.1	96.6 (± 0.7)	90.0	65.8	91.0	82.3 (± 0.7)	92.3	63.5	89.7	81.8 (± 0.9)
		FT	8.0	7.5	4.7	6.7(± 0.2)	1.4	0.7	4.1	2.1(± 0.1)	2.2	1.3	1.5	1.7(± 0.1)
		KN	0.5	0.7	0.9	0.7(± 0.1)	0.7	0.7	0.4	0.6(± 0.1)	0.3	0.8	0.4	0.5(± 0.1)
		ROME	10.1	11.2	22.7	14.7(± 0.4)	34.1	22.8	68.7	41.9(± 1.2)	6.4	4.9	5.7	5.7(± 0.1)
		MEMIT	1.1	1.1	1.4	1.2(± 0.1)	1.0	1.0	4.2	2.1(± 0.1)	0.6	0.9	0.7	0.7(± 0.1)
		KE	0.7	0.7	0.8	0.7(± 0.1)	0.7	0.7	1.2	0.9(± 0.1)	0.8	0.8	0.7	0.8(± 0.1)
		MEND	0.7	0.7	0.8	0.7(± 0.1)	0.7	0.7	0.8	0.7(± 0.1)	0.7	0.7	0.7	0.7(± 0.1)
		MALMEN	54.8	52.5	66.0	57.8(± 0.9)	48.6	23.1	47.9	39.9(± 0.6)	42.1	32.4	39.2	37.9(± 0.7)
	100	DAFNET	85.2	72.7	94.3	84.1(± 1.4)	73.3	42.2	77.1	64.2(± 1.1)	58.2	41.9	88.2	62.8(± 1.7)
		AlphaEdit	76.0	60.4	81.7	72.7(± 1.0)	62.4	35.8	60.6	52.9(± 1.4)	48.5	36.9	81.6	55.7(± 0.9)
		TP	46.6	42.0	10.4	33.0(± 0.5)	70.5	41.5	5.2	39.1(± 0.8)	45.2	29.6	12.3	29.0(± 0.7)
		GRACE	9.8	9.2	23.7	14.2(± 0.5)	32.1	21.8	69.7	41.2(± 1.0)	6.2	5.5	5.8	5.8(± 0.2)
		MELO	73.4	59.3	81.2	71.3(± 0.8)	54.1	32.7	57.6	48.1(± 1.2)	47.7	36.8	75.9	53.5(± 0.7)
		LTE	78.7	63.4	83.2	75.1(± 1.6)	68.0	40.1	65.8	58.0(± 1.3)	53.9	40.2	82.6	58.9(± 1.1)
		QueueEDIT	89.0	77.7	98.1	88.3 (± 1.0)	76.8	45.7	84.9	69.1 (± 0.7)	65.4	46.2	90.3	67.3 (± 0.8)

Table 5: Results of QueueEDIT and baselines with 10 and 100 edits.