PMET: Precise Model Editing in a Transformer

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Abstract

Model editing techniques modify a minor proportion of knowledge in Large Language Models (LLMs) at a relatively low cost, which have demonstrated notable success. Existing methods assume Transformer Layer (TL) hidden states are values of key-value memories of the Feed-Forward Network (FFN). They usually optimize the TL hidden states to memorize target knowledge and use it to update the weights of the FFN in LLMs. However, the information flow of TL hidden states comes from three parts: Multi-Head Self-Attention (MHSA), FFN, and residual connections. Existing methods neglect the fact that the TL hidden states contains information not specifically required for FFN. Consequently, the performance of model editing decreases. To achieve more precise model editing, we analyze hidden states of MHSA and FFN, finding that MHSA encodes certain general knowledge extraction patterns. This implies that MHSA weights do not require updating when new knowledge is introduced. Based on above findings, we introduce PMET, which simultaneously optimizes Transformer Component (TC, namely MHSA and FFN) hidden states, while only using the optimized TC hidden states of FFN to precisely update FFN weights. Our experiments demonstrate that PMET exhibits state-of-the-art performance on both the COUNTERFACT and zsRE datasets. Our ablation experiments substantiate the effectiveness of our enhancements, further reinforcing the finding that the MHSA encodes certain general knowledge extraction patterns and indicating its storage of a small amount of factual knowledge. Our code is available at https://github.com/xpq-tech/PMET.git.

1 Introduction

Large language models (LLMs), as an emerging form of knowledge base (Petroni et al., 2019; Heinzerling and Inui, 2021; Cao et al., 2021), are extensively employed worldwide, primarily addressing queries through knowledge recall.

Nonetheless, these models are often criticized for furnishing erroneous information (Ji et al., 2023; Zhao et al., 2023). The cost of fine-tuning or training from scratch to correct the minor proportion of erroneous knowledge is frequently deemed impractical. Fortunately, recent model editing techniques have demonstrated the ability to modify minor proportion of knowledge in LLMs with relatively low cost (Meng et al., 2022b; Mitchell et al., 2022a; Yao et al., 2023). Model editing aims to modify the internal knowledge of LLMs without resorting to vanilla training or fine-tuning. The success rates of model editing in edited-knowledge and in knowledge related to the edited-knowledge are assessed separately based on efficacy and generalization, while the preservation of irrelevant editedknowledge is measured by specificity (also known as locality) (Mitchell et al., 2022a). For the purpose of uniformity, we collectively refer to efficacy and generalization as reliability. Additionally, two metrics are employed to evaluate the generative capacity of the post-edited model: fluency and consistency (Meng et al., 2022a). Model editing methods can be classified into two categories based on whether the original model weights are modified: weight-preserved and weight-modified methods (Yao et al., 2023). Weight-preserved methods often require additional content, whereas weightmodified methods directly edit model weights without the need for extra content, making them a more lightweight alternative.

The weight-modified approaches include learning-based (Sinitsin et al., 2020; Mitchell et al., 2022a) and optimization-based methods (Meng et al., 2022b,a). Learning-based methods utilize gradient information to update the weights, but they suffer from poor knowledge generalization and are prone to overfitting. The optimization-based method ROME (Meng et al., 2022a) views Feed-Forward Network (FFN) as key-value memories (Geva et al., 2021) and alleviates this

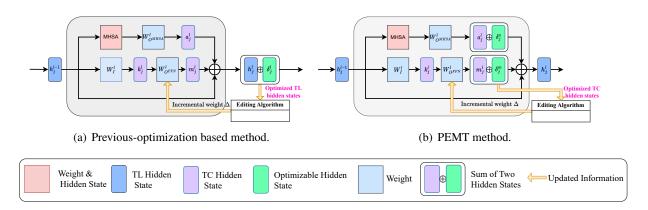


Figure 1: Comparison between PMET and existing methods in a Transformer layer. (a) Existing optimization-based methods employ optimized TL hidden states to perform vague updates on FFN weights. (b) PMET simultaneously optimizes the TC hidden states of both MHSA and FFN, but only uses the optimized TC hidden states of FFN to perform precise updates on FFN weights.

issue by optimizing Transformer Layer (TL) hidden states to memorize target knowledge and updating FFN weights incrementally. The subsequent MEMIT (Meng et al., 2022b) follows the same way and further improves ROME, enabling the editing of thousands to millions of pieces of knowledge in a single operation and demonstrating impressive editing success rates and generalization capabilities. However, the information flow of TL hidden states comes from three parts: Multi-Head Self-Attention (MHSA), FFN, and residual connections. Both ROME and MEMIT use optimized TL hidden states as the target knowledge representations for updating FFN weights, which overlooks the irrelevant information within the TL hidden states that is not required by FFN, resulting in imprecise updating of weights based on non-accurate target knowledge representations and compromising editing performance. To address this issue, we suggest optimizing the Transformer Component (TC, namely MHSA and FFN) hidden states directly of FFN to memorize target knowledge for precise updates on FFN weights.

But unexpectedly, during the practical process of directly optimizing the TC hidden states of FFN, we encounter occasional optimization bottlenecks where the TC hidden states can not be aligned with target knowledge. We attribute this phenomenon to the limitations imposed by the function space of the TC hidden states of FFN. A plausible solution to address this is the supplementary optimization of TC hidden states within MHSA. However, this introduces a novel inquiry: whether MHSA, like FFN, possesses the capability to store factual knowledge

(Geva et al., 2021), necessitating updates to its weights. In pursuit of this inquiry, we endeavor to analyze hidden states of MHSA and FFN to determine the role of MHSA in LLMs' knowledge recall. We then observe that the knowledge contained within MHSA undergoes more frequent changes compared to that within FFN. Combining previous findings of MHSA (Geva et al., 2023; Wang et al., 2022; Hassid et al., 2022) with our observation, we believe that MHSA works as a knowledge extractor and stores certain general knowledge extractor and stores certain general knowledge extraction patterns. This suggests the potential for supplementary optimization of TC hidden states of the MHSA to expand the function space, without necessitating updates to its weights.

Based on the above finding, we propose PMET, which simultaneously optimizes TC hidden states of MHSA and FFN, utilizing solely the optimized TC hidden states of FFN as the target knowledge representations for updating FFN weights, enabling precise updates. The differences between PMET and existing methods are illustrated in Figure 1. Our experiments demonstrate that PMET exhibits state-of-the-art comprehensive performance in editing GPT-J (6B) (Wang and Komatsuzaki, 2021) and GPT-NeoX (20B) (Black et al., 2022) on the zsRE and COUNTERFACT datasets. Specifically, in COUNTERFACT dataset, PMET shows a 3.3% average reliability enhancement over the state-ofthe-art method, while in zsRE dataset, it achieves a 0.4% average improvement. Furthermore, our series of ablation experiments demonstrate that our enhancements are effective and PMET strikes a good balance among reliability, specificity, fluency, and consistency. To sum up, our main contributions

are as follows:

- We reveal that the MHSA works as a knowledge extractor, encodes certain general knowledge extraction patterns, and stores a small amount of factual knowledge.
- We propose PMET, which leverages the general knowledge extraction patterns of MHSA and simultaneously optimizes the TC hidden states of MHSA and FFN to memorize target knowledge. However, PMET only uses the optimized TC hidden states of FFN to update FFN weights due to the unnecessary updates to MHSA weights.
- Our experiments with GPT-J (6B) on the zsRE and counterfact datasets highlight PMET's superiority across multiple dimensions. Additionally, editing GPT-NeoX (20B) on the COUNTERFACT dataset underscores PMET's superior reliability and consistency over exsiting methods.

2 Related Work

2.1 Model editing

Model editing is an emerging field in recent years, mainly aimed at mitigating the high cost of model training. Model editing methods can be classified into two categories: weight-modified and weightpreserved(Mitchell et al., 2022b; Zheng et al., 2023; Hernandez et al., 2023). Weight-preserved methods typically achieve this preservation by introducing external models (Mitchell et al., 2022b), utilizing in-context learning (Zheng et al., 2023), or altering the LLMs' representation space (Hernandez et al., 2023). These approaches effectively safeguard nontarget knowledge while modifying the target knowledge. However, as the number of knowledge modifications increases, the required additional content also grows substantially. In contrast, weightmodified methods (Sinitsin et al., 2020; Mitchell et al., 2022a; Meng et al., 2022b,a) directly modify the model weights for editing, thereby avoiding the aforementioned content increasing issue. Initially, weight-modified methods use approaches like multi-loss fine-tune (Sinitsin et al., 2020) and constrained fine-tune (Zhu et al., 2020). Yet these methods often suffer from overfitting. To address this issue, researchers later proposed meta-learning methods (De Cao et al., 2021; Mitchell et al., 2022a) and optimization-based methods (Meng

et al., 2022a). Nevertheless, as the number of edited-knowledge increases, the efficacy and generalization of these methods deteriorate significantly. This challenge is tackled by MEMIT (Meng et al., 2022b), which further improves ROME and enable edit a large amount of knowledge in one go. The optimization-based methods are built upon the conclusion that FFN are key-value memories (Geva et al., 2021) and update FFN weights by optimizing the TL hidden states to memorize target knowledge. While these methods have achieved some success in model editing, they confuse the information flow among the MHSA, FFN, and residual connections, leading to a non-accurate updates on FFN weights. In contrast to these methods, PMET simultaneously optimizes the TC hidden states of MHSA and FFN to memorize target knowledge, while only use the optimized TC hidden states of FFN, facilitating precise updates of FFN weights.

2.2 Post-hoc Explanation of Transformers

Post-hoc explanation is a broad field, and our focus is on understanding the roles of the two components, MHSA and FFN, in Transformers (Kovaleva et al., 2019; Wang et al., 2022; Hassid et al., 2022; Geva et al., 2022; Kobayashi et al., 2023; Hao et al., 2021; Geva et al., 2023). Currently, it is widely believed that FFN serves as the main carrier for storing factual knowledge(Geva et al., 2021; Meng et al., 2022a,b), and each layer of FFN contributes to knowledge recall(Geva et al., 2022, 2023). MHSA is primarily responsible for capturing the degree of association between different tokens, focusing on interactions between content (Hao et al., 2021; Kobayashi et al., 2023), and extracting attributes of subjects (Geva et al., 2023). Other studies have shown that MHSA contains different levels of redundant information (Wang et al., 2022; Hassid et al., 2022). These findings imply that MHSA may store certain general patterns used for knowledge extraction. However, they do not completely clarify this and fail to provide insights into whether MHSA stores factual knowledge. We endeavor to analyze the hidden states of MHSA and FFN to explore these.

3 Methodology

3.1 Preliminaries

Language Modeling. We focus on autoregressive, decoder-only LLMs denoted as \mathcal{F}_{θ} . These models transform the input sequence x into z to-

kens $x_1, ..., x_z$ and then input them into L layers of Transformer decoders to obtain the probabilities of the next token x_{z+1} as follows:

$$\mathcal{F}_{\theta}(x_1, ..., x_z) = \operatorname{softmax} \left(W_{\mathsf{E}} \gamma \left(h_z^{L-1} + a_z^L + m_z^L \right) \right)$$
$$= \mathbb{P} \left(x_{z+1} | x_1, ..., x_z \right)$$

Here, W_E and γ represent the embedding matrix and layernorm, respectively, and a_z^L and m_z^L are the TC hidden states of the MHSA and FFN of the L-th layer, respectively. Note that the MHSA and FFN in (1) are parallel (Wang and Komatsuzaki, 2021; Black et al., 2022). The general forms of the MHSA and FFN at the l-th layer and the j-th token x_j^l are given by:

$$\begin{split} a_{j}^{l} &= W_{O^{\text{MHSA}}}^{l} \text{MHSA}^{l} \left(h_{1}^{l-1}, h_{2}^{l-1}, ..., h_{j}^{l-1} \right), \\ m_{j}^{l} &= W_{O^{\text{FFN}}}^{l} \sigma \left(W_{I}^{l} \gamma \left(h_{j}^{l-1} \right) \right) \end{split}$$

Here, $W_{O^{\rm MHSA}}^l$ and $W_{O^{\rm FFN}}^l$ are the output weights of the MHSA and FFN at the l-th layer, respectively, and σ represents the non-linear activation function. We have omitted bias terms for simplicity.

Model Editing problem. Previous researches on model editing have been limited to defining the problem solely based on editing the triples (i.e., subject-relation-object) themselves (Meng et al., 2022a; Mitchell et al., 2022b), overlooking the knowledge contained within the triples. Consequently, the edited models are unable to reason based on the edited knowledge (Cohen et al., 2023). In this paper, we redefine the model editing problem from a subject-centric perspective, where the edited knowledge is associated with the subject, aiming to enable the edited models to reason based on the subject.

Let \mathcal{F}_{θ} be an LLM that has learned N pieces of knowledge related to subject S, represented by the set:

$$K^{S} = \left\{ \left\{ \boldsymbol{x}_{i}^{S}, \boldsymbol{y}_{i}^{S} \right\}, i \in \{0, 1, 2, ..., N\} \right\} \quad (3)$$

Here, \boldsymbol{x}_i^S and \boldsymbol{y}_i^S represent the knowledge clue sequence and the knowledge point sequence, respectively, for the i-th piece of knowledge. The LLM \mathcal{F}_{θ} satisfies: $\mathcal{F}_{\theta}\left(\boldsymbol{x}_i^S\right) = \boldsymbol{y}_i^S, \forall i \in \{0,1,2,...,N\}.$ The objective of model editing is to modify N' pieces of knowledge in the LLM related to subject S to the target knowledge:

$$K^{S_t} = \left\{ \left\{ \boldsymbol{x}_i^{S_t}, \boldsymbol{y}_i^{S_t} \right\}, i \in \left\{0, 1, 2, ..., N'\right\} \right\}$$
 (4)

while keeping the $M(M\gg N)$ pieces of knowledge in the set

$$K^{\neg S_t} = \left\{ \left\{ \boldsymbol{x}_j^{\neg S_t}, \boldsymbol{y}_j^{\neg S_t} \right\}, j \in \{0, 1, 2, ..., M\} \right\}$$
(5)

that are unrelated to the N' pieces of model learned knowledge. Hence, the edited LLM \mathcal{F}_{θ^*} should satisfy:

$$\mathcal{F}_{\theta^*}\left(\boldsymbol{x}_i^{S_t}\right) = \boldsymbol{y}_i^{S_t} \wedge \mathcal{F}_{\theta^*}\left(\boldsymbol{x}_j^{\neg S_t}\right) = \boldsymbol{y}_j^{\neg S_t},$$

$$\forall i \in \left\{0, 1, 2, ..., N'\right\}, j \in \left\{0, 1, 2, ..., M\right\}.$$
(6)

The evaluation metrics for model editing can be found in Appendix A.1.

3.2 Investigating the role of MHSA and FFN in LLMs' knowledge recall

Inspired by Geva et al. (Geva et al., 2023), who analyzed critical subject information by mapping intermediate topic representations to vocabulary tokens, we compare the differences of hidden states h_z^{l-1} and a_z^l of the last token before and after (i.e., input and output) flowing through the l-th layer MHSA, both in the vector space and the vocabulary space. Similarly, we perform the same analysis on the hidden states h_z^{l-1} and m_z^l of the last token before and after flowing through the l-th layer FFN.

We use 1209 factual statements from (Meng et al., 2022a) as knowledge queries to explore the knowledge contained within GPT-J (6B). The last token position of each query aggregates the information of the entire query; thus, we consider the hidden state of the last token of each query as a representation of the key knowledge related to that query from the LLMs. We hypothesis a positive correlation between the similarity of hidden states and the consistency of knowledge. To measure the similarity, we calculate the cosine similarity of hidden states and the Jaccard similarity (Murphy, 1996) of the mapping to vocabulary tokens. Specifically, we extract the hidden states of the last token before and after each layer of MHSA and FFN, compute their cosine similarity, and obtain the top-k tokens in the vocabulary. Subsequently, we calculate the Jaccard similarity between the topk tokens of the intermediate states before and after the process. The Jaccard similarity is defined as follows:

$$J_k(T(h_1), T(h_2)) = \frac{|T(h_1) \cap T(h_2)|}{|T(h_1) \cup T(h_2)|}$$
(7)

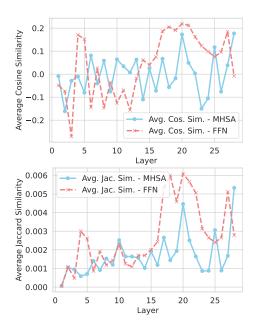


Figure 2: The changes in the average cosine similarity and average Jaccard similarity of the hidden states before and after MHSA and FFN.

where $T(h_1)$ and $T(h_2)$ represent the top-k mappings of the hidden states h_1 and h_2 on the vocabulary, respectively. We set k=50 in our experiments.

The average changes in cosine and Jaccard similarities of the last tokens from 1209 factual statements across all layers and components of GPT-J are shown in Figure 2. In the first 15 layers of GPT-J, both the MHSA and FFN exhibit relatively frequent changes in their hidden states. However, after the 15th layer, the intermediate states of the FFN undergo a slower rate of change, gradually stabilizing in a specific direction. While the hidden states of the MHSA continue to undergo frequent changes, and their directions remain uncertain throughout the knowledge extraction of GPT-J. Considering our hypothesis regarding the relationship between hidden states and knowledge, this phenomenon suggests that the knowledge contained in FFN's hidden states tends to become consistent after a certain period, while the knowledge contained in MHSA's hidden states undergoes frequent changes throughout knowledge recall of GPT-J. We attribute this observation to the fact that the MHSA continuously extracts various types of knowledge, while the FFN primarily extracts its own knowledge (Geva et al., 2021; Meng et al., 2022a). Furthermore, considering previous findings regarding the extraction of attributes from the MHSA with observed redundancies (Geva et al., 2023; Wang et al., 2022; Hassid et al., 2022), we believe that the MHSA works as a knowledge extractor and stores certain general knowledge extraction patterns.

3.3 PMET Method

PMET first computes the target knowledge representations in FFN of critical layers by simultaneously optimizing the TC hidden states of both MHSA and FFN. Subsequently, PMET updates FFN weights in the critical layers through target knowledge representations. PMET optimizes an objective function to obtain target weights (Meng et al., 2022b):

$$W_{1} \triangleq \underset{W}{\operatorname{argmin}} \left(\sum_{i=1}^{n} \|Wk_{i} - v_{i}\|^{2} + \sum_{i=n+1}^{n+u} \|Wk_{i} - v_{i}\|^{2} \right). \tag{8}$$

Here, $k_i riangleq k_i^l$ and $v_i riangleq v_i^l$ represent the sets of keys and values, respectively, encoding the subject-related knowledge in the l-th layer. $\sum_{i=1}^n \|Wk_i - v_i\|^2$ indicates that we want to retain n pieces of knowledge, while $\sum_{i=n+1}^{n+u} \|Wk_i - v_i\|^2$ indicates that we want to modify $u \gg 1$ pieces of knowledge. We represent the keys and values as matrices stacked horizontally: $[k_1 \mid k_2 \mid \cdots \mid k_n] \triangleq K$ and $[v_1 \mid v_2 \mid \cdots \mid v_n] \triangleq V$, and we consider the target weight W_1 as the sum of the original weight W_0 and the incremental weight Δ , i.e., $W_1 = W_0 + \Delta$. Based on the derivation from MEMIT (Meng et al., 2022b), the formal expression for the incremental weight is:

$$\Delta = RK_1^T (C_0 + K_1 K_1^T)^{-1}, \tag{9}$$

where $R \triangleq V_1 - W_0 K_1$ represents the residual between the values V_1 (namely target knowledge representations) corresponding to the keys K_1 of the target knowledge and the model original knowledge $W_0 K_1$. $C_0 \triangleq K_0 K_0^T = \lambda \cdot \mathbb{E}_k \left[k k^T \right]$ is an estimate of the set of previously memorized keys obtained through sampling. Here, λ is a hyperparameter which balances the degree of model modification and preservation.

As an example, let's consider modifying the N' knowledge instances K^S related to the subject S in LLMs to the target knowledge K^{S_t} . Assuming that the set of previously memorized keys C_0 has already been obtained through sampling, and knowledge clues \boldsymbol{x}_i^S have been inputed into the original model to obtain W_0K_1 , we then need the sets of keys and values for the target knowledge,

denoted as K_1 and V_1 , respectively. Similar to MEMIT, we calculate the target knowledge set of the last critical layer $L = \max(\mathcal{R})$. Throughout this paper, we mainly use h_i^L , m_i^L , a_i^L , and δ_i to represent the hidden states of the last tokens of the subject S in the knowledge clues x_i^S .

Unlike ROME and MEMIT, which add optimizable parameters δ_i to the TL hidden states h_i^L at the L-th layer (as shown in Figure 1 (a)) and obtain the optimized TL hidden states $v_i = h_i^L + \delta_i$ through gradient descent, PMET adds optimizable parameters δ^a_i and δ^m_i to the TC hidden states a^L_i and m_i^L of the components (i.e., MHSA and FFN) at the L-th layer, respectively. Then, PMET only retains the optimized TC hidden states of FFN to update FFN weights, denoted as $v_i^m = m_i^L + \delta_i^m =$ argmin $\mathcal{L}(v_i^m)$ (as shown in Figure 1 (b)). $\mathcal{L}(v_i^m)$ is defined as follows:

$$\mathcal{L}(v_i^m) \qquad \text{lines varies with the num} \\ = \mu * D_{\text{KL}} \left(\mathbb{P}_{\mathcal{F}_{\theta}\left(a_i^L += \delta_i^a, m_i^L += \delta_i^m\right)} \left[\boldsymbol{y} \mid p' \right] \| \mathbb{P}_{\mathcal{F}_{\theta}} \left[\boldsymbol{y} \mid p' \right] \right) + \\ \varphi * \frac{1}{P} \sum_{j=1}^{P} -\log \mathbb{P}_{\mathcal{F}_{\theta}\left(a_i^L += \delta_i^a, m_i^L += \delta_i^m\right)} \left[\boldsymbol{y}_i^{S_t} \mid \text{pref}_j \oplus p(\boldsymbol{x_i}) \right], \text{are defined as follows:}$$

hyperparameters and μ are used to balance reliability and specificity. $\mathcal{F}_{\theta}\left(a_{i}^{L}+=\delta_{i}^{a},m_{i}^{L}+=\delta_{i}^{m}\right)$ represents the optimizable parameters δ_i^a and δ_i^m are added to the TC hidden states of MHSA and FFN at the L-th layer of the model \mathcal{F}_{θ} , respectively. $\operatorname{pref}_{j} \oplus p(\boldsymbol{x_i})$ and p' are, as in (Meng et al., 2022a,b), prefixes used to enhance the generalization of the target knowledge and the prompt template used for calculating the KL divergence: $\{S\}$ is a'. After calculating the values of all the target knowledge that need to be changed, they can be stacked into a matrix V_1 .

To edit multiple layers of the model, we need to spread the residual R to all critical layers. MEMIT spreads updates evenly over the range of critical layers \mathcal{R} as $R^l = \frac{V_1 - W_0 K_1}{L - l + 1}$. In contrast, PMET adopts a square root spread to convey more precise information to critical layers:

$$R^{l} = \frac{V_1 - W_0 K_1}{\sqrt{L - l + 1}}. (11)$$

Now that we have C_0 and R^l , the next step is to obtain keys K_1 . Keys are related to specific weights to be edited and represent the hidden states before entering those specific weights. Similar to (Meng et al., 2022a,b), the keys k_i^l at the l-th layer

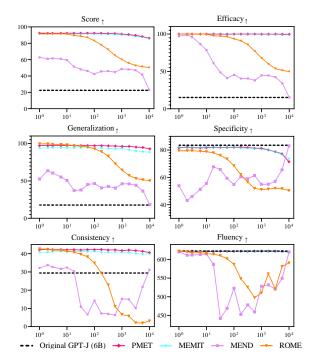


Figure 3: The editing performance of PMET and baselines varies with the number of edits (X-axis).

$$k_i^l = \frac{1}{P} \sum_{j=1}^{P} \operatorname{prev}(W, \operatorname{pref}_j \oplus S), \qquad (12)$$

where $\operatorname{prev}(W, \operatorname{pref}_i \oplus S)$ represents the hidden state of the input $\operatorname{pref}_{i} \oplus S$ before flowing through the weight W. If one wants to edit $W_{O^{\mathrm{FFN}}}^{l}$ in (2), then $\operatorname{prev}(W_{O^{\text{FFN}}}^{l}, x) = \sigma\left(W_{I}^{l} \gamma\left(h_{j}^{l-1}\left(x\right)\right)\right).$

With this, PMET follows the same algorithm steps as MEMIT to update FFN weights.

Experiments

Baselines and Datasets

Our experiments are conducted on GPT-J (6B) and GPT-NeoX (20B). Our baseline methods include the improved Constrained Fine-Tuning (FT+W) (Zhu et al., 2020; Meng et al., 2022b), the learningbased method MEND (Mitchell et al., 2022a), and the optimization-based methods ROME (Meng et al., 2022a) and MEMIT (Meng et al., 2022b). For the datasets, we performed counterfactual update experiments on two datasets: Zero-Shot Relation Extraction (zsRE) (Levy et al., 2017) and COUNTERFACT (Meng et al., 2022a). More details about the datasets can be found in Appendix A.2.

Editor	Score	Efficacy	Generalization	Specificity	Fluency	Consistency
GPT-J	22.4	15.2 (0.7)	17.7 (0.6)	83.5 (0.5)	622.4 (0.3)	29.4 (0.2)
FT-W	67.6	99.4 (0.1)	77.0 (0.7)	46.9 (0.6)	293.9 (2.4)	15.9 (0.3)
MEND	23.1	15.7 (0.7)	18.5 (0.7)	83.0 (0.5)	618.4 (0.3)	31.1 (0.2)
ROME	50.3	50.2 (1.0)	50.4 (0.8)	50.2 (0.6)	589.6 (0.5)	3.3 (0.0)
MEMIT	85.8	98.9 (0.2)	88.6 (0.5)	73.7 (0.5)	619.9 (0.3)	40.1 (0.2)
PMET	86.2	99.5 (0.1)	92.8 (0.4)	71.4 (0.5)	620.0 (0.3)	40.6 (0.2)
GPT-NeoX	23.7	16.8 (1.9)	18.3 (1.7)	81.6 (1.3)	620.4 (0.6)	29.3 (0.5)
MEMIT	82.0	97.2 (0.8)	82.2 (1.6)	70.8 (1.4)	606.4 (1.0)	36.9 (0.6)
PMET	84.3	98.4 (0.2)	89.4 (0.5)	70.3 (0.5)	598.1 (0.6)	38.9 (0.2)

Table 1: 10,000 counterfact edits on GPT-J (6B) and GPT-NeoX (20B). Within parentheses is the 95% confidence interval.

4.2 Editing Experiments

The score is the harmonic mean of efficacy, generalization, and specificity, representing the balance between reliability (i.e., efficacy and generalization) and specificity of the editing method(Meng et al., 2022a). Note that in our experiments, we updates counterfactual information, so we evaluated specificity based on factual information, while when testing for efficacy and generalization, we used counterfactual information as the standard. As a result, the unedited LLMs performed poorly in terms of efficacy and generalization but exhibited good performance in terms of specificity. For detailed implementation details, please refer to Appendix A.3.

4.2.1 Editing Knowledge in COUNTERFACT

As mentioned in (Meng et al., 2022a), we also conducted 17 counterfactual experiments by sampling 17 integers $n_i = \exp\left(\ln{(10000)} * \frac{i}{16}\right)$ from a log-scale curve for editing. The performance of PMET and other existing methods on GPT-J (6B) in these 17 edits is shown in Figure 3. With the exception of being slightly inferior to MEMIT in terms of specificity, PMET outperforms all baselines in all other metrics.

Table 1 presents the results of all methods on 10K counterfactual edits. The results show that PMET outperforms existing methods in score, efficacy, fluency, and consistency, but is slightly inferior to MEMIT in specificity, and like MEMIT, it is far behind the meta-learning based method MEND. In the trade-off between editing reliability and specificity, both PMET and MEMIT tend to

Editor	Efficacy	Generalization	Specificity
GPT-J	26.4 (±0.6)	$25.8~(\pm 0.5)$	$27.0~(\pm 0.5)$
FT-W	69.6 (±0.6)	64.8 (±0.6)	24.1 (±0.5)
MEND	$19.4~(\pm 0.5)$	$18.6 \ (\pm 0.5)$	$22.4~(\pm 0.5)$
ROME	$21.0 \ (\pm 0.7)$	$19.6 (\pm 0.7)$	$0.9 (\pm 0.1)$
MEMIT	96.7 (± 0.3)	$89.7 (\pm 0.5)$	$26.6 (\pm 0.5)$
PMET	$96.9(\pm 0.3)$	90.6 (± 0.2)	26.7 (± 0.2)

Table 2: 10,000 zsRE Edits on GPT-J (6B).

prioritize reliability, while MEND leans towards specificity. While sacrificing some specificity for improved reliability is acceptable until better methods are available, we hope to find a compromise in the future.

Then, we applied PMET to conduct 10K edits on GPT-NeoX (20B) on the COUNTERFACT dataset, and the results are shown in the lower part of Table 1. Similarly, PMET outperforms MEMIT in terms of reliability and consistency, but lags behind in specificity and fluency. These might be because PMET employs square root propagation (11), resulting in greater changes to the model and hence more damage to specificity and fluency. We further investigate this in the following ablation experiments. Nevertheless, these results demonstrate that PMET achieves the most significant updates to target knowledge compared to existing methods.

4.2.2 Editing 10K Knowledge in zsRE

The results of editing 10K knowledge instances on the zsRE dataset are presented in Table 2. The results demonstrate that PMET outperforms existing methods in all three metrics: efficacy, generaliza-

Edits	Editor	Score	Efficacy	Generalization	Specificity	Fluency	Consistency
	GPT-J	22.4	15.2	17.7	83.5	622.4	29.4
1K	$\begin{array}{c} {\rm PMET} \\ {\rm w/o} \ \delta^a_i \\ {\rm w/} \ W^l_{O^{\rm MHSA}} \\ {\rm Even \ spread} \end{array}$	91.1 90.8 (\$\dagger\$0.3) 90.8 (\$\dagger\$0.3) 88.9 (\$\dagger\$2.2)	99.8 99.6 (↓0.2) 99.8 (→) 99.6 (↓0.2)	96.1 96.6 (†0.5) 96.8 (†0.7) 86.7 (\$\dagger*)99	80.1 79.1 (↓1.0) 78.9 (↓1.2) 82.2 (↑ 3.1)	622.2 622.4 (†0.2) 622.0 (↓0.2) 622.3 (↓0.1)	41.7 42.2 (\(\daggered{\gamma}\)0.5) 42.1 (\(\daggered{\gamma}\)0.4) 39.1 (\(\daggered{\gamma}\)3.1)
5623	$\begin{array}{c} {\rm PMET} \\ {\rm w/o} \ \delta^a_i \\ {\rm w/} \ W^l_{O^{\rm MHSA}} \\ {\rm Even \ spread} \end{array}$	88.0 87.0 (\1.0) 86.7 (\1.3) 85.8 (\2.2)	99.7 99.3 (\dot 0.4) 99.6 (\dot 0.1) 98.2 (\dot 1.5)	94.5 95.0 (†0.5) 96.0 (†1.5) 82.2 (\ldot\)12.3)	74.2 72.0 (\dagger*2.2) 70.8 (\dagger*3.4) 79.4 (\dagger*5.2)	621.7 622.3 (†0.6) 621.3 (↓0.4) 621.8 (†0.1)	41.3 41.6 (†0.3) 41.6 (†0.3) 38.1 (\dagger 3.2)
10K	PMET w/o δ^a_i w/ $W^l_{O^{\mathrm{MHSA}}}$ Even spread	86.2 85.0 (\pm1.2) 84.9 (\pm1.3) 83.3 (\pm2.9)	99.5 98.9 (\downarrow 0.6) 99.5 (\rightarrow) 96.7 (\downarrow 2.8)	92.8 89.0 (↓3.8) 93.5 (↑0.7) 78.4(↓ 14.4)	71.4 71.6 (\(\gamma\)0.2) 68.6 (\(\jepsilon\)2.8) 77.3 (\(\gamma\)5.9)	620.0 621.2 (†1.2) 619.0 (↓1.0) 621.8 (†1.8)	40.6 40.0 (\dagger 0.6) 40.5 (\dagger 0.1) 37.4 (\dagger 3.2)

Table 3: The results of the ablation experiments. w/o δ^a_i represents only optimizing the TC hidden state δ^m_i of FFN. w/ $W^l_{O^{\rm MHSA}}$ represents simultaneously updating the weights of both MHSA and FFN. Even spread represents evenly spreading the residual R to the critical layers \mathcal{R} .

tion, and specificity. It is worth noting that the original GPT-J (6B) model has a specificity score of only 27.0, and therefore, the specificity of the edited models is also lower than this value.

4.3 Ablation Study

We conduct three sets of ablation experiments and demonstrate that: 1) PMET simultaneously optimizing the TC hidden states of MHSA and FFN can result in enhanced reliability; 2) The updating of MHSA weights contributes marginally to the improved generalization of editing while also inflicting greater damage to specificity; and 3) square root spreads in PMET enhances reliability but leads to larger changes in the model, ultimately affecting specificity. All the ablation experiments were conducted on COUNTERFACT using GPT-J (6B), with parameters consistent with the previous experiments in COUNTERFACT.

We first conduct experiments where PMET only optimizes TC hidden states of FFN (i.e., δ^a_i is removed) for 1K, 5623, and 10K counterfactual edits. The experimental results are shown in Table 3 under "w/o δ^a_i ". This shows that simultaneously optimizing TC hidden states of FFN and MHSA can result in better reliability compared to only optimizing TC hidden states of FFN.

Next, we update the weights of both MHSA and FFN using the optimized TC hidden states. This means we updated $W_{O^{\rm MHSA}}^l$ and $W_{O^{\rm FFN}}^l$ simultaneously in (2), and additionally computed the keys for (12) as $\operatorname{prev}(W_{O^{\rm MHSA}}^l,x)=$

MHSA l $\left(h_1^{l-1}\left(x\right),h_2^{l-1}\left(x\right),...,h_j^{l-1}\left(x\right)\right)$. The results are shown in Table 3 under "w/ $W_{O^{\mathrm{MHSA}}}^l$ ". The results indicate that additionally updating MHSA weights can slightly improve editing generalization, but at the same time, it worsens the specificity. This might be due to the fact that MHSA weights store certain general knowledge extraction patterns along with a small amount of factual knowledge. While updating MHSA weights strengthens the extraction patterns of the knowledge similar to edited-knowledge, it may also impair the patterns of extracting other unrelated knowledge, making it more likely to harm specificity.

Finally, we evenly spread the residual R to the critical layers \mathcal{R} , and the results are shown in Table 3 under "Even spread". The results indicate that even spreading leads to better model retention (i.e., better specificity and fluency), but efficacy, generalization, and consistency are much worse compared to square root spreading. This suggests that using even spreading in PMET may cause significant loss of update information, reducing the update reliability while preserving more of the model's original knowledge. In other words, using square root spreading mitigates the loss of update information, improves reliability, but leads to larger changes in the model, causing more side effects to the specificity and fluency.

We further analyze the relationship between the editing performance and the norms of the incremental weight Δ in Appendix A.4. In summary, PMET

strikes a good balance between reliability and specificity, and this balance becomes more pronounced as the number of edited knowledge increases.

5 Conclusion

We reveal that MHSA works as a knowledge extractor and encodes certain general knowledge extraction patterns. Based on this finding, we propose PMET, which simultaneously optimizes the TC hidden states of both MHSA and FFN while only uses the optimized TC hidden states of FFN to perform precise updates of FFN weights. Our experiments on zsRE and COUNTERFACT demonstrate the stateof-the-art performance of PMET. Furthermore, our ablation experiments show that our enhancements are effective, PMET strikes a good balance between different metrics, and MHSA stores a small amount of factual knowledge. Our findings contribute additional insights for a better comprehension of the roles played by MHSA and FFN, and our approach takes a step forward in terms of model editing techniques.

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A Appendix

A.1 Metrics of Model Editing Problem

Based on the subject-centric model editing problem, two evaluation metrics naturally emerge: reliability and specificity. Reliability aims to assess the success rate of the edited model on all knowledge related to the target knowledge, while specificity, also known as locality (Mitchell et al., 2022b), aims to evaluate the success rate of the edited model on knowledge sets unrelated to the target knowledge. However, evaluating the success on all knowledge related or unrelated to the target knowledge is currently challenging. Previous works (Meng et al., 2022a,b) divided reliability into efficacy and generalization, evaluating the success rate of the edited model on edit sequences and paraphrase edit sequences, respectively. The paraphrase edit sequences and edit sequences are semantically consistent, while differing in syntax.

To adapt the definition of subject-centric model editing problem to existing metrics and datasets, we divide the knowledge set related to subject S into explicit and implicit knowledge sets:

$$\begin{split} K^{S_t^{\text{exp.}}} &= \left\{ \left\{ \boldsymbol{x}_q^{S_t^{\text{exp.}}}, \boldsymbol{y}_q^{S_t^{\text{exp.}}} \right\}, q \in \{0, 1, 2, ..., Q\} \right\} \\ K^{S_t^{\text{imp.}}} &= \left\{ \left\{ \boldsymbol{x}_p^{S_t^{\text{imp.}}}, \boldsymbol{y}_p^{S_t^{\text{imp.}}} \right\}, q \in \{0, 1, 2, ..., P\} \right\} \end{split}$$

where P + Q = N' and $P \gg Q$. Explicit knowledge set consists of knowledge clue and knowledge point pairs directly shown in the text, while implicit knowledge set contains a large number of knowledge derived from the corresponding explicit knowledge. For instance, for the subject 'Forbidden City,' an explicit knowledge clue may be: "Forbidden City is located in," with explicit knowledge point: "Beijing." An implicit knowledge clue corresponding to this explicit knowledge could be: "If you want to go to Forbidden City, you need to take a plane from New York to," with the implicit knowledge point: "Beijing." Another implicit knowledge clue could be: "The place where Forbidden City is located in is China's", with the knowledge point: "capital." The explicit knowledge set and implicit knowledge set correspond to existing edit sequences and paraphrase edit sequences, respectively. Formally, efficacy, generalization, and specificity can be represented as:

• Efficacy:

$$\mathbb{E}_{\left\{\boldsymbol{x}_{p}^{S_{t}^{\exp}},\boldsymbol{y}_{p}^{S_{t}^{\exp}}\right\} \in K^{S_{t}^{\exp}}} \mathbf{1}[\max_{\boldsymbol{y}} \left(\mathbb{P}_{\mathcal{F}_{\boldsymbol{\theta}^{*}}}(\boldsymbol{y}|\boldsymbol{x}_{p}^{S_{t}^{\exp}})\right) = \boldsymbol{y}_{p}^{S_{t}^{\exp}}]$$

$$\tag{14}$$

• Generalization:

$$\mathbb{E}_{\left\{\boldsymbol{x}_{q}^{S_{t}^{\text{imp.}}},\boldsymbol{y}_{q}^{S_{t}^{\text{imp.}}}\right\} \in K^{S_{t}^{\text{imp.}}}} \mathbf{1}[\max_{\boldsymbol{y}} \left(\mathbb{P}_{\mathcal{F}_{\boldsymbol{\theta}^{*}}}(\boldsymbol{y}|\boldsymbol{x}_{q}^{S_{t}^{\text{imp.}}})\right) = \boldsymbol{y}_{q}^{S_{t}^{\text{imp.}}}]$$
(15)

• Specificity:

$$\mathbb{E}_{\left\{\boldsymbol{x}_{j}^{\neg St},\boldsymbol{y}_{j}^{\neg St}\right\} \in K^{\neg St}} \mathbf{1} \left[\max_{\boldsymbol{y}} \left(\mathbb{P}_{\mathcal{F}_{\boldsymbol{\theta}^{*}}}(\boldsymbol{y} | \boldsymbol{x}_{j}^{\neg St})\right) = \boldsymbol{y}_{j}^{\neg St}\right]$$
(16)

Additionally, Meng et al. (Meng et al., 2022a,b) also employed the metrics of fluency and consistency to assess the generation capability of the edited models, and our work also takes these two metrics into consideration.

A.2 Datasets Detail

For the sake of fairness in testing, we use the same datasets as in MEMIT (Meng et al., 2022b), which include zsRE and COUNTERFACT. zsRE is a question-answering dataset used to evaluate the correction ability of editing methods. For example, as shown in Figure 4, the goal of the editing method is to change the knowledge about the subject "Watts Humphrey" in LLMs from "Trinity College" to "University of Michigan," so that the edited model can answer the explicit question "src" (explicit knowledge) and the implicit question "rephrase" (implicit knowledge) correctly about this knowledge, without affecting the answer to "loc." Table 2 reports efficacy, which reflects the success rate of the edited model in answering explicit questions, generalization, which reflects the success rate in answering implicit questions, and specificity, which reflects the success rate in answering "loc." The COUNTERFACT dataset has similar testing benchmarks to zsRE for the first three items. However, COUNTERFACT has more than one "paraphrase," and "loc" (i.e., "neighborhood_prompts" in COUNTERFACT). For more details, please refer to COUNTERFACT datasets (Meng et al., 2022a). Additionally, the COUNTERFACT dataset also contains "generation_prompts," a set of prompts containing subjects, which is used to evaluate the generation capability of the edited model, corresponding to the fluency and consistency metrics.

A.3 Experimental Detail

The critical layers for GPT-J and GPT-NeoX have been identified as $\mathcal{R} = \{3, 4, 5, 6, 7, 8\}$ and $\mathcal{R} = \{6, 7, 8, 9, 10\}$ (Meng et al., 2022a,b). Therefore, we mainly update these critical layers of GPT-J and GPT-NeoX. All the baselines we compare, including the parameter settings of MEMIT, are consistent with (Meng et al., 2022b).

For the optimization of the TC hidden states in GPT-J and GPT-NeoX, we initially set $\varphi=\mu=1$. When maximizing the probability of the target knowledge, we want to preserve the model's original knowledge as much as possible, so we set $\psi=0.1$ and stop the optimization when $D_{\mathrm{KL}}\left(\mathbb{P}_{\mathcal{F}_{\theta}\left(a_{i}^{L}+=\delta_{i}^{a},m_{i}^{L}=v_{i}^{m}\right)}\left[\boldsymbol{y}\mid\boldsymbol{p}'\right]\|\mathbb{P}_{\mathcal{F}_{\theta}}\left[\boldsymbol{y}\mid\boldsymbol{p}'\right]\right)<0.01.$

estimate of the set of previously memorized keys obtained through sampling

On GPT-J, for the covariance matrix (i.e., the set of previously memorized keys C_0) estimation, we sampled 10K times on Wikitext in fp32 precision and set $\lambda=6000$ ($\lambda=4500$ in zsRE). When optimizing the TC hidden states δ^a_i and δ^m_i , we set the total optimization steps to 30 steps with a learning rate of 0.2 (20 steps with a learning rate of 0.5 in zsRE), and limit them, as in MEMIT, to have their norms less than $\frac{3}{4}$ of the norms of the original intermediate states.

On GPT-NeoX, we sampled 5K times on Wikitext in fp16 precision and stored the covariance matrix in fp32 precision, with $\lambda=15000$. For optimization, we set the total optimization steps to 30 steps with a learning rate of 0.5, and limit them to have their norms less than $\frac{4}{5}$ of the norms of the original intermediate states.

As the algorithmic steps of PMET are fundamentally similar to MEMIT, the time consumption of the two methods is almost equivalent.

A.4 Analysis of Incremental Weight

In the ablation experiments discussed in Section 4.3, we have demonstrated that PMET strikes a good balance between reliability and specificity. In this section, we further analyze the relationship between the editing performance and the norms of the incremental weight obtained in the corresponding ablation experiments. The changes in the incremental weight norms for each case are illustrated in Figure 5.

Firstly, it is evident that the norms of incremental weight for updating the MHSA weights (i.e.,

Preprint. Under review. A APPENDIX

```
{"subject": "Watts Humphrey",
"src": "What university did Watts Humphrey attend?",
"pred": "Trinity College",
"rephrase": "What university did Watts Humphrey take part in?",
"alt": "University of Michigan",
"answers": ["Illinois Institute of Technology"],
"loc": "nq question: who played desmond doss father in hacksaw ridge",
"loc_ans": "Hugo Weaving",
"cond": "Trinity College >> University of Michigan || What university did Watts Humphrey attend?"}
```

Figure 4: A sample of the zsRE dataset

 $W_{O^{
m MHSA}}^l$ (MHSA)) and the even spread case are significantly smaller than those for the other cases. In GPT-J, the the MHSA weights are 0.25 times the FFN weights, so the smaller norms for the MHSA weights are expected. The reason for the smaller norms in the even spread case is that the magnitude of the residuals R is reduced more in this case compared to the square root spread case, resulting in the loss of a considerable amount of update information during the spreads of residuals, thereby compromising the reliability of the editing process. However, this information loss favors the preservation of the original model.

Secondly, the incremental weight norms for PMET, w/o δ_i^a , and w/ $W_{O{\rm MHSA}}^l$ (FFN) are very close to each other, consistent with the findings presented in Table 3, where these three cases exhibit similar editing performance. A closer examination reveals that the incremental weight norm for PMET is the smallest among the three cases, but at the same time, PMET achieves the best overall performance. This implies that the incremental weight obtained in PMET are the most accurate in capturing the updates needed for the desired editing.

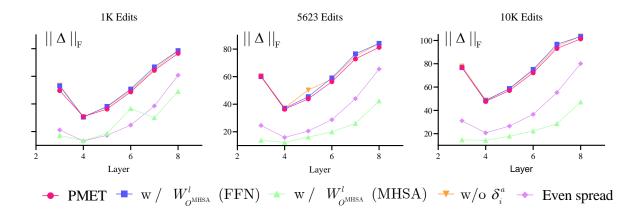


Figure 5: The norm changes of the incremental weight Δ in the ablation experiment.