Model Editing Can Hurt General Abilities of Large Language Models

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Abstract

Recent advances in large language models (LLMs) have opened up new paradigms for accessing the knowledge stored in their parameters. One critical challenge that has emerged is the presence of hallucinations in LLM outputs due to false or outdated knowledge. Since retraining LLMs with updated information is resource-intensive, there has been a growing interest in model editing. However, many model editing methods, while effective in various scenarios, tend to overemphasize aspects such as efficacy, generalization, and locality in editing performance, often overlooking potential side effects on the general abilities of LLMs. In this paper, we raise concerns that the improvement of model factuality may come at the cost of a significant degradation of these general abilities, which is not conducive to the sustainable development of LLMs. Systematically, we analyze side effects by evaluating four popular editing methods on two LLMs across eight representative task categories. Extensive empirical research reveals that model editing does improve model factuality but at the expense of substantially impairing general abilities. Therefore, we advocate for more research efforts to minimize the loss of general abilities acquired during LLM pre-training and to ultimately preserve them during model editing.

1. Introduction

As real-world knowledge is dynamically increasing and updating, existing large language models (LLMs) need to be upgraded timely to incorporate the latest knowledge to stay at the forefront of the field. For example, the ChatGPT gpt-3.5-turbo API has already updated its lastest

The code is available at https://github.com/JasonForJoy/Model-Editing-Hurt

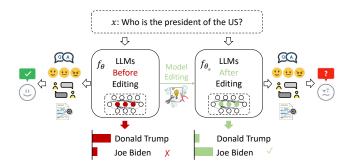


Figure 1. Demonstration of model editing and its impact on the general abilities of LLMs. Although the factuality of the model has been improved, it is unclear whether the original general abilities of LLMs, such as question answering, sentiment analysis, dialogue, information extraction, etc, can be preserved after editing. f_{θ} / f_{θ_e} denotes the models before / after editing.

knowledge from September 2021 to January 2022. Despite continual training, LLMs inevitably manifest hallucinations caused by false or outdated knowledge embedded in their parameters (Zhang et al., 2023; Peng et al., 2023; Ji et al., 2023). This phenomenon leads to a degradation in system performance, often falling short of meeting user expectations in various real-world scenarios. Due to the resource-intensive cost of retraining LLMs, there has been a growing interest in *model editing* (a.k.a., *knowledge editing*) (Sinitsin et al., 2020; Cao et al., 2021; Dai et al., 2022; Mitchell et al., 2022b; Meng et al., 2022; 2023; Yao et al., 2023; Zhong et al., 2023; Ma et al., 2023; Zhang et al., 2024). This task targets at enabling data-efficient alterations to model behavior, specifically within a designated realm of interest, while ensuring no adverse impact on other inputs.

Current methods designed for the alteration of model parameters can be broadly classified into two paradigms, reflecting distinct approaches to the modification and optimization of model editing (Wang et al., 2023; Yao et al., 2023). Specifically, they are based on either meta-learning (Cao et al., 2021; Mitchell et al., 2022a) or locate-then-edit (Dai et al., 2022; Meng et al., 2022; 2023). At present, the assessment of an editing method typically involves a comprehensive evaluation along three

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¹https://chat.openai.com/share: When it comes to the latest world knowledge, ChatGPT has changed its expression to "As of my last knowledge update in January 2022".

critical dimensions. First and foremost is *efficacy*, aiming to ascertain the capability of the post-edited model to accurately recall the specific editing fact. The second dimension *generalization* seeks to validate the adaptability of the edited model by assessing its ability to recall the editing fact under diverse paraphrase prompts. The last dimension *locality* (a.k.a., *specificity*) is employed to verify the stability of the edited model by examining whether its output for unrelated inputs remains consistent after editing. These multi-faceted criteria collectively contribute to a nuanced understanding of the effectiveness and robustness of each editing method.

While numerous model editing methods have demonstrated their effectiveness across a spectrum of scenarios, a noteworthy concern lies in their inclination to place disproportionate emphasis only on enhancing editing performance. Regrettably, this focus often occurs without adequate consideration for potential side effects on the underlying general abilities of LLMs. In this paper, we put forward a critical concern regarding the overall robustness and adaptability of the edited models in real-world applications. It is questionable whether such improvements of model factuality come at the significant cost of compromising general abilities of LLMs such as summarization (Gliwa et al., 2019), question answering (QA) (Kwiatkowski et al., 2019), natural language inference (Dagan et al., 2005), etc. If model editing hurts general abilities of LLMs, this trade-off poses a substantial challenge to the sustainable development of LLMs. We argue that research in this field should not fall into the trap of penny-wise and pound foolish, as the pursuit of improvement in model factuality must be balanced against the imperative need for models to maintain their effectiveness across a diverse range of tasks.

In light of the above issues, we systematically study if model editing hurts general abilities of LLMs in this paper. Through extensive empirical research, the side effects of four popular editing methods including KN (Dai et al., 2022), MEND (Mitchell et al., 2022a), ROME (Meng et al., 2022), and MEMIT (Meng et al., 2023) are analyzed by evaluating them based on two representative LLMs of different sizes including GPT-2 XL (1.5B) (Radford et al., 2019), and LLaMA-1 (7B) (Touvron et al., 2023a). Eight representative task categories including reasoning (Cobbe et al., 2021), natural language inference (Dagan et al., 2005), open-domain QA (Kwiatkowski et al., 2019), closed-domain QA (Clark et al., 2019a), dialogue (Cui et al., 2020), summarization (Gliwa et al., 2019), named entity recognition (Sang & Meulder, 2003), and sentiment analysis (Socher et al., 2013) are employed to extensively demonstrate the impact of model editing on general abilities of LLMs.

Experimental findings indicate that although model editing is a promising research direction that can update the factual

knowledge encapsulated within the parameters of LLMs in a resource-efficient and target-specific way, current editing methods still have significant flaws in preserving the original general abilities. In fact, there exists an important but often overlooked premise: model editing should strive to improve the model factuality to help mitigate hallucinations without compromising its existing general abilities. However, the ongoing research trend excessively pursues the efficacy, generalization and locality of editing, while significantly damaging the original general abilities of LLMs. This seems to have fallen into the trap of penny-wise (i.e., improvement of model factuality) and pound-foolish (i.e., loss of general abilities), which should not happen and should be avoided at all costs. This paper advocates for a particular viewpoint and points out the urgent shortcomings in the field of model editing, calling for follow-up research efforts to improve the factuality and preserve the general abilities of LLMs simultaneously.

2. Related Work

Model Editing Many studies have investigated model editing, including memory-based, meta-learning, and locatethen-edit (Wang et al., 2023; Yao et al., 2023). Memorybased methods do not modify model weights but store the editing facts with an external memory (Mitchell et al., 2022b; Zhong et al., 2023). For example, Mitchell et al. (2022b) stored edits in a base model and learned to reason over them to adjust its predictions as needed. The latter two classes of methods are developed to directly modify the internal parameters of models, which is the focus of this paper. On the one hand, meta-learning methods train a hypernetwork to get gradient changes to update model parameters (Cao et al., 2021; Mitchell et al., 2022a). Cao et al. (2021) utilized a hypernetwork to predict parameter shift at test time. Mitchell et al. (2022a) learned to transform the fine-tuning gradient into a low-rank decomposition of the gradient. On the other hand, locate-then-edit methods first locate knowledge neurons in LLMs that exhibit a positive correlation with a knowledge expression, and then modify them accordingly (Dai et al., 2022; Meng et al., 2022; 2023). In particular, Dai et al. (2022) computed the contribution of each neurons to a certain knowledge, then updated or erased knowledge by modifying these neurons with the embedding vectors of facts. Meng et al. (2022) located multi-layer perceptron (MLP) storing factual knowledge, and then edited such knowledge by injecting new key-value pair in the MLP module. Besides, some works investigate the paradigm for the evaluation of model editing (Zhong et al., 2023; Cohen et al., 2023; Ma et al., 2023; Li et al., 2023; Hase et al., 2023; Wu et al., 2023a; Gandikota et al., 2023). For example, Cohen et al. (2023) introduced the ripple effects of model editing, suggesting that editing a particular fact implies that many other facts

need to be updated. Additionally, some recent works have also applied this approach in various domains, such as changing model personality (Mao et al., 2023), editing multimodal models (Cheng et al., 2023), protecting users privacy (Wu et al., 2023b), etc.

Interpretability of Transformer Many studies have attempted to explain and understand Transformer (Vaswani et al., 2017). Previous works focus on the function of selfattention layers and the differences between layers (Tenney et al., 2019; Vig & Belinkov, 2019; Voita et al., 2019; Clark et al., 2019b). For instance, Voita et al. (2019) found that the most confident attention heads played consistent linguistically-interpretable roles. More recently, a surge of works have investigated the role of feed-forward network (FFN) layers in Transformer, showing that FFN layers store factual and linguistic knowledge, which can be located in specific neurons and edited (Geva et al., 2021; Da et al., 2021; Meng et al., 2022; Dai et al., 2022). Besides, Geva et al. (2022) investigated the mechanism in which FFN layers update the inner representations of Transformer-based LMs. They propose that the FFN output can be viewed as a collection of updates that promote concrete concepts in the vocabulary space.

Compared with previous studies (Dai et al., 2022; Meng et al., 2022; 2023; Mitchell et al., 2022a; Yao et al., 2023) that are the most relevant to our work, a main difference should be highlighted. These approaches target at designing editing algorithms or evaluation paradigms to improve or assess the performance of model editing in terms of efficacy, generalization and locality. In contrast, this study rethinks model editing and explores if current editing methods inadvertently cause potential side effects on the underlying general abilities of LLMs. To the best of our knowledge, this paper makes the first call for attention to side effects on a variety of tasks beyond editing performance by presenting a systematical evaluation of four editing methods on two LLMs covering eight task categories. It reveals a surprising finding that such improvements of model factuality by current editing methods come at the significant cost of compromising general abilities of LLMs.

3. Preliminaries

3.1. Language Model

Training language models (LMs) on extensive text corpora has resulted in significant advancements in downstream tasks. In the process of acquiring linguistic understanding, these LMs may inadvertently capture and retain relational knowledge inherent in the training data, enabling them to respond to queries effectively (Petroni et al., 2019). With the increasing popularity of GPT series models (Brown et al., 2020; Chen et al., 2021; Ouyang et al., 2022), recent

research on model editing has worked on autoregressive LMs (Meng et al., 2022; 2023; Zhong et al., 2023), which is also the focus of this study. Basically, such autoregressive LMs generate text by iteratively sampling from a conditional token distribution $\mathcal{P}(x_t|x_1,x_2,...,x_{t-1})$ parameterized by an L-layer Transformer-based language model \mathcal{LM} as:

$$\mathcal{P}(x_t|x_1, x_2, ..., x_{t-1}) = \mathcal{LM}(x_1, x_2, ..., x_{t-1})$$

$$= \operatorname{softmax}(W^V h_{t-1}^L),$$
(1)

where h_{t-1}^L denotes the hidden state representation at the final layer L and ending token t-1, and W^V denotes the vocabulary embedding table. This state representation is computed using the following recursive relation:

$$h_t^l = h_t^{l-1} + a_t^l + m_t^l, (2)$$

$$a_t^l = \text{ATTEN}(h_1^{l-1}, h_2^{l-1}, ..., h_t^{l-1}), \tag{3}$$

$$m_t^l = FFN(h_t^{l-1}), (4)$$

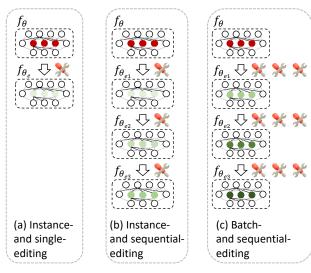
where h_t^0 denotes the embedding of token x_t . Note that the attention (ATTEN) and feed-forward network (FFN) layers are written in parallel following Wang & Komatsuzaki (2021) and Black et al. (2022), and layer normalization is omitted for easy understanding.

3.2. Model Editing

Model editing involves modifying the memorized facts contained in LMs without retraining to better suit specific tasks or requirements. Various kinds of complex learned beliefs such as logical, spatial, or numerical knowledge are expected to be edited. In this paper, we study editing factual knowledge in the form of (subject s, relation r, object o), e.g., (s = United States, r = President of, o = Donald Trump). An LM is expected to recall a memory and predict the next token(s) representing o given a natural language prompt p(s,r) such as "The President of the United States is". Editing a fact is to insert a new knowledge triple (s,r,o^*) in place of the current one (s,r,o), where these two triples share the same subject and relation. An editing operation is represented as $e = (s,r,o,o^*)$ for brevity.

Given a set of editing facts $\mathcal{E} = \{e_1, e_2, \ldots\}$ and a model f, model editing involves learning a function K that yields an edited language model $f^*: K(f, \mathcal{E}) = f^*$. To evaluate the effectiveness of various model editing methods, previous works focus on evaluation along three dimensions: efficacy, generalization and locality (Cao et al., 2021; Mitchell et al., 2022a; Meng et al., 2022; 2023).

Efficacy Given an editing fact (s = United States, r = President of, o = Donald Trump, $o^* = Joe Biden$), it could be regarded edited effectively if the edited model f^* assigns a higher probability to the statement "The President of the United States is Joe Biden" than the original prediction (Donald Trump).



💥 : An instance of editing fact

Figure 2. Illustration of the settings of (a) single- and instance-editing, (b) sequential- and instance-editing, and (c) sequential- and batch-editing. The darker units correspond to more edits.

Generalization Edited models should be able to recall the updated knowledge when prompted within the editing scope. For example, the paraphrased prompts like "Who currently holds the office of President of the United States?" or "Who is the current president of the US?" can be used. The edited model f^* is considered to have generalized successfully if it can recall the editing memory, in this case, "Joe Biden".

Locality The edited model f^* should remain unchanged in response to prompts that are irrelevant or outside the scope of its editing. For example, the answer to the question "Who is the President of France?" should still correctly be "Emmanuel Macron".

4. Methodology

To extensively demonstrate the effect of model editing, this paper systematically rethinks model editing in the *single*- versus *sequential*-editing settings (Section 4.1), as well as in the *instance*- versus *batch*-editing settings (Section 4.2). Figure 2 illustrates these experimental settings for easy understanding. Afterwards, these edited models are evaluated on a variety of downstream tasks to see if there are any side effects on performance before and after editing.

4.1. Single- vs. Sequential-editing

Single-editing This concept involves examining the impact and efficacy of making a single editing operation to a model, and focuses on understanding how a model adapts to such a single alteration. It is worth noting that a single editing operation can contain either only one editing

instance or multiple ones in a batch, which will be further discussed in Section 4.2. In practice, there are common scenarios where only a specific modification is required, and it is essential to understand how well the model incorporates and maintains that single edit. Specifically, the goal is to explore how the behavior of a model is influenced by a single editing operation, and to understand the implicit effect of such specific modifications on the overall performance of edited models. Therefore, evaluating the effectiveness of a single edit is crucial in determining the robustness of a model and its ability to retain the intended changes.

Sequential-editing In contrast to single-editing, multiple editing operations are conducted successively in sequentialediting (Huang et al., 2023). Similarly, each editing operation in sequential-editing can also contain either only one editing instance or multiple ones in a batch. Whether the edited model can still maintain its original general abilities after sequential editing is one of the important characteristics that should be considered when evaluating the effectiveness of an editing method. Ideally, models should retain the changes from previous edits when carrying out a new one (Yao et al., 2023), which is decisive for the sustainable development of future LLMs. For this analysis, models are edited in a stream of editing operations successively, and how the performance of edited models on a variety of tasks changes as the number of edits increases will be explored.

4.2. Instance- vs. Batch-editing

Instance-editing It refers to using only one instance per editing operation to make specific and targeted adjustments to individual pieces of knowledge within LLMs, regardless of the single- or sequential-editing settings. This setting is particularly valuable in situations where certain instances present unique challenges or outliers that require specialized treatment. These fine-grained alterations to model behaviors over individual instances are expected to contribute to more adaptable and accurate LLMs.

Batch-editing The real world is ever-changing, so there is a huge amount of knowledge that needs to be dynamically added and updated into LLMs. Despite the effectiveness of many methods designed for instance-editing (Dai et al., 2022; Meng et al., 2022; Ma et al., 2023), ultimately at most a few dozens of pieces of knowledge can be updated (Mitchell et al., 2022b), due to their relatively low but still non-negligible editing cost for a single instance. Since naive sequential applications of current state-of-the-art model editing methods fail to scale up (Meng et al., 2023), one may wish to update hundreds or thousands of facts simultaneously in batch-editing. Notably, batchediting can also be coupled with both the single- or sequential-editing settings.

Table 1. Comparisons between several popular model editing methods following Yao et al. (2023). Additional Training refers to whether the methods need training before conducting specific edits. Batch Edit refers to editing multiple target knowledge simultaneously. Editor Parameters refers to the parameters that need to be updated for editing. L denotes the number of layers to update. MLP is FFN and MLP_{proj} is the second linear layer in FFN. neuron denotes the key-value pair in FFN.

Paradigm	Editing Methods	Additional Training	Batch Edit	Editor Parameters
Meta-learn	MEND	Yes	Yes	$Model_{hyper} + L*MLP$
Locate-	KN	No	No	L*neuron
then-	ROME	No	No	MLP_{proj}
edit	MEMIT	No	Yes	$L*MLP_{proj}$

4.3. Zero-shot Learning

Zero-shot learning aims to solve unseen tasks without labeled training examples. More recent work has demonstrated the superiority of LLMs for zero-shot learning (Brown et al., 2020; Wei et al., 2022; Chowdhery et al., 2023). Following these studies, we explore the zero-shot learning performance of edited models on a variety of tasks in this work. Given a task instruction and a test problem that are concatenated as the input, the model is expected to generate a target text to address the test problem. The instructions and input formats of different tasks are taken from or inspired by Qin et al. (2023).

5. Experiments

We briefly introduced the experimental setup regarding editing methods, editing datasets, selected LLMs, and representative tasks in this section. Readers can refer to their corresponding papers for more details.

5.1. Editing Methods

Four popular model editing methods as compared in Table 1 were selected to measure their performance in improving factuality as well as their impairment in general abilities of LLMs, including:

KN (Dai et al., 2022)² first selected neurons that were associated with knowledge expression via gradient-based attributions, and then modified MLP layer at the rows corresponding to those neurons by adding scaled embedding vectors.

MEND (Mitchell et al., 2022a)³ learned a hypernetwork to produce weight updates by decomposing the fine-tuning gradients into rank-1 form.

ROME (Meng et al., 2022)⁴ first localized the factual knowledge at a specific layer in the transformer MLP modules, and then updated the knowledge by directly writing new key-value pairs in the MLP module.

MEMIT (Meng et al., 2023)⁵ expanded the capabilities of ROME by enabling the editing of large amounts of factual data through the updating of a sequence of MLP layers.

All experiments were conducted using the EasyEdit tool (Wang et al., 2023), ensuring standardized and reproducible evaluation. All editing instances were randomly sampled from the editing dataset.

5.2. Editing Datasets

The popular model editing dataset Zero-Shot Relation Extraction (ZsRE) (Levy et al., 2017) used in previous work (Cao et al., 2021; Meng et al., 2022; Yao et al., 2023) was adopted in our experiments. ZsRE is a QA dataset using question rephrasings generated by backtranslation as the equivalence neighborhood. Each input is a question about an entity, and plausible alternative edit labels are sampled from the top-ranked predictions of a BART-base model trained on ZsRE. Experiments on the COUNTERFACT (Meng et al., 2022) will be released soon.

5.3. Selected LLMs

Experiments were conducted on two LLMs of different sizes including **GPT-2 XL** (1.5B) (Radford et al., 2019), and **LLaMA-1** (7B) (Touvron et al., 2023a). Experiments on more LLMs will be released soon.

5.4. Tasks, Datasets and Metrics

To explore whether model editing has side effects on general abilities of LLMs, eight representative task categories were adopted for assessment, including:

Reasoning on the GSM8K (Cobbe et al., 2021), and the results were measured by solve rate.

Natural language inference (NLI) on the RTE (Dagan et al., 2005), and the results were measured by accuracy of two-way classification.

Open-domain QA on the Natural Question (Kwiatkowski et al., 2019), and the results were measured by exact match (EM) with the reference answer after minor normalization as in Chen et al. (2017) and Lee et al. (2019).

Closed-domain QA on the BoolQ (Clark et al., 2019a), and the results were also measured by EM.

Dialogue on the MuTual (Cui et al., 2020), and the results

²https://github.com/EleutherAI/knowledge-neurons

³https://github.com/eric-mitchell/mend

⁴https://github.com/kmeng01/rome

⁵https://github.com/kmeng01/memit

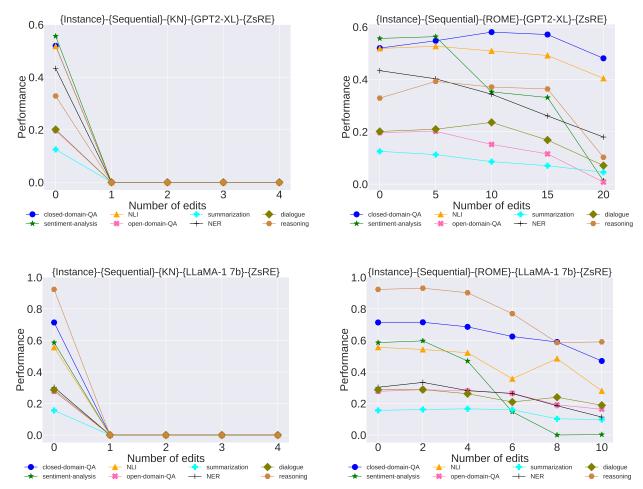


Figure 3. Performance on general tasks of edited models using KN (Dai et al., 2022) or ROME (Meng et al., 2022) to edit GPT2-XL (Radford et al., 2019) or LLaMA-1 (7B) (Touvron et al., 2023b) as the number of edits increases in *instance- and sequential-editing*.

were measured by selecting one best-matched response from four available candidates, denoted as Recall₄@1 as in Lowe et al. (2015).

Summarization on the SAMSum (Gliwa et al., 2019), and the results were measured by the average of ROUGE-1, ROUGE-2 and ROUGE-L as in Lin (2004).

Named entity recognition (NER) on the CoNLL03 (Sang & Meulder, 2003), and the results were measured by entity-level F1-score.

Sentiment analysis on the SST2 (Socher et al., 2013), and the results were measured by accuracy of two-way classification.

6. Results and Analysis

6.1. Impact of Instance- and Sequential-editing

Since instance- and single-editing can be regarded as a special case of instance- and sequential-editing when the number of edits is 1, this subsection mainly discussed instance- and sequential-editing. KN (Dai et al., 2022) and ROME (Meng et al., 2022) that supported instanceediting but not batch-editing were adopted to facilitate this exploration in this setting. Figure 3 presents the performance on general tasks of edited models using KN or ROME to edit GPT2-XL (Radford et al., 2019) or LLaMA-1 (7B) (Touvron et al., 2023b) as the number of edits increases. It can be seen that although there is only one instance per editing operation to make specific and targeted adjustments to LLMs, the performance of the edited models on various tasks fluctuates significantly and shows a downward trend as the number of edits increases. Strikingly, the use of KN to edit LLaMA-1 (7B) resulted in a drastic performance degradation to nearly 0 with just a single edit. These findings underscore two key insights. On the one hand, these results indicate that the selected LLMs, particularly LLaMA-1 (7B), are not robust to weight updates, whereby slight perturbations and attacks may significantly affect their general task performance. On the other hand, these

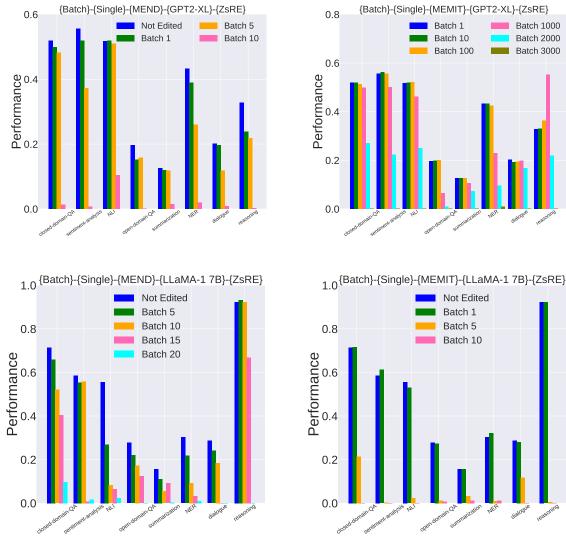


Figure 4. Performance on general tasks of edited models using MEND (Mitchell et al., 2022a) or MEMIT (Meng et al., 2023) to edit GPT2-XL (Radford et al., 2019) or LLaMA-1 (7B) (Touvron et al., 2023b) with different batch sizes in batch- and single-editing.

outcomes also shed light on the challenging nature of effectively coupling current editing algorithms with LLMs. The difficulty lies in the dual objective of improving model factuality while simultaneously maintaining general abilities. The observed trends indicate that existing editing algorithms face grand challenges in achieving this delicate balance, emphasizing the need for further research and development in the refinement of editing methodologies for LLMs.

6.2. Impact of Batch Size on Editing

To effectively scale up the scope of editing, the incorporation of batch editing becomes a pivotal technique, enabling editing multiple target knowledge instances simultaneously. Therefore, this subsection delved into batch- and single-editing to explore the impact of batch size on editing.

MEND (Mitchell et al., 2022a) and MEMIT (Meng et al., 2023) that supported batch-editing were adopted to facilitate this exploration in this setting. Figure 4 presents the performance on general tasks of edited models using MEND or MEMIT to edit GPT2-XL or LLaMA-1 (7B) with different batch sizes. As the batch size varies, the performance change of edited models provide valuable insights into how batch-editing influences the general abilities of models across diverse tasks. Remarkably, even with only one single editing operation, the performance of edited models exhibits a trend of performance degradation as the batch size increases in most cases. This consistent decrease in performance underlines the sensitivity of the models to increases in batch size, emphasizing the significance of carefully scaling knowledge editing for optimal updates. It is obvious that current editing algorithms cannot maintain

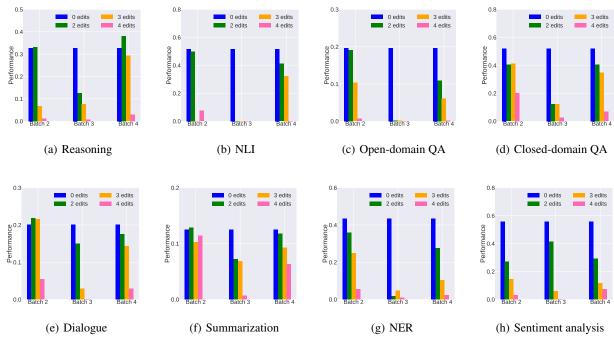


Figure 5. Performance on general tasks of edited models using MEND (Mitchell et al., 2022a) to edit GPT2-XL (Radford et al., 2019) as the number of edits increases in *batch- and sequential-editing*.

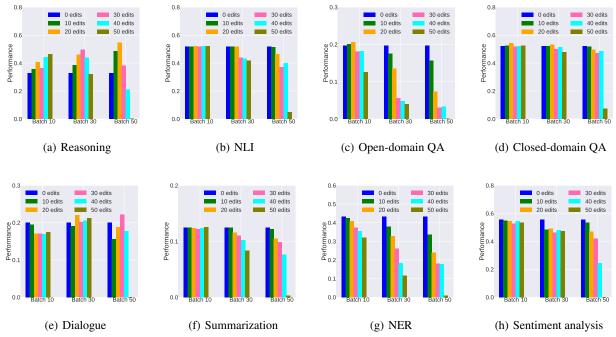


Figure 6. Performance on general tasks of edited models using MEMIT (Meng et al., 2023) to edit GPT2-XL (Radford et al., 2019) as the number of edits increases in batch- and sequential-editing.

robust and satisfactory results when applied in large-scale editing scenarios. Therefore, we call for more research work on meticulous design of scalable editing to facilitate the efficient editing of enabling multiple editing instances concurrently.

6.3. Impact of Batch- and Sequential-editing

In order to holistically take into account the interplay between batch size and sequential-editing effects on model editing, a combined setting of batch- and sequentialediting was explored to understand how these two factors

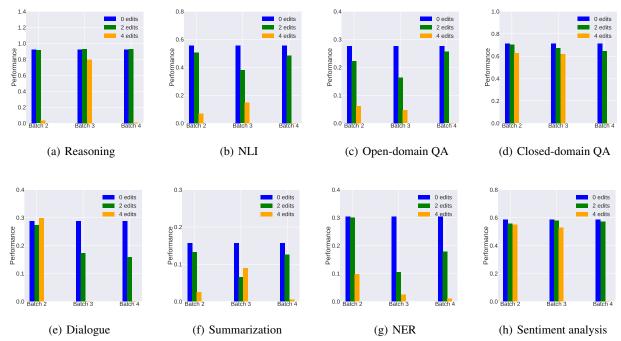


Figure 7. Performance on general tasks of edited models using MEND (Mitchell et al., 2022a) to edit LLaMA-1 (7B) (Touvron et al., 2023b) as the number of edits increases in *batch- and sequential-editing*.

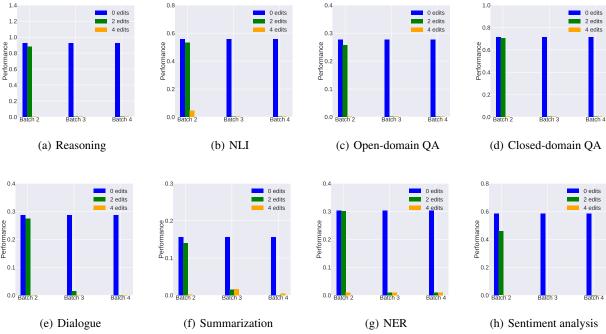


Figure 8. Performance on general tasks of edited models using MEMIT (Meng et al., 2023) to edit LLaMA-1 (7B) (Touvron et al., 2023b) as the number of edits increases in batch- and sequential-editing.

collaboratively influence the overall performance of edited models. Figure 5 and Figure 6 present the performance on general tasks of edited models using MEND or MEMIT to edit GPT2-XL (Radford et al., 2019) respectively as the number of edits increases. Similarly, Figure 7 and Figure 8

present the performance of using MEND or MEMIT to edit LLaMA-1 (7B) (Touvron et al., 2023b) respectively. The results echo our observations in Section 6.1 on instance- and sequential-editing, and those in Section 6.2 on batch- and single-editing.

7. Conclusion and Discussion

The rapid development of model upgrading technology has been catalyzing the continuous iteration of more advanced and trustworthy LLMs. Model editing is promising and has been attracting increasing attention as a resourceefficient and target-specific way to update the knowledge encapsulated within the parameters of LLMs. Although many existing studies have presented promising results demonstrating improvements in editing performance, this paper rethinks model editing and for the first time raises a concern whether model editing has any side effects on general abilities of LLMs. To confirm our concerns, the side effects are analyzed by systematically evaluating four popular editing methods on two LLMs covering eight representative task categories. Evaluation results remarkably reveals that although current editing methods can effectively improve editing performance, they inevitably hurt general abilities of LLMs no matter in instance- or batch-editing, and single- or sequential-editing.

In addition to the aforementioned considerations, this paper calls on the community to pay attention to and underscores the collective focus on several pivotal areas within the field of language model editing.

Strengthen the robustness of LLMs to weight updates. There is a pressing demand to strengthen LLMs to withstand the influence of subtle perturbations and potential adversarial attacks without compromising their general task performance. Addressing this challenge is pivotal for

adversarial attacks without compromising their general task performance. Addressing this challenge is pivotal for ensuring the reliability and resilience of LLMs in practical applications across various domains.

Develop innovative editing paradigms. The object is to not only enhance the factuality of LLMs but also to concurrently sustain and improve their general abilities. By exploring new editing paradigms, researchers can open up possibilities for refining the precision of information generated by LLMs, making them more adept at capturing and producing reliable outputs.

Design comprehensive evaluation on model editing. Establishing a systematic and thorough framework for assessing the effectiveness of a model editing method is essential to gauge the success of proposed enhancements accurately. This probably includes defining and implementing rigorous standards for evaluating the factual accuracy, overall performance on general tasks, and adaptability of LLMs post-editing. Such a comprehensive evaluation methodology will contribute significantly to the establishment of a robust benchmark, facilitating meaningful comparisons and advancements in the field.

In essence, this paper urges the research community to prioritize efforts in enhancing LLMs against weight updates, exploring new editing paradigms, and designing comprehensive evaluation methodologies. By doing so, we can collectively advance the understanding and abilities of LLMs, paving the way for more reliable and versatile applications in diverse real-world scenarios.

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