

# Neuron Patching: Neuron-level Model Editing on Code Generation and LLMs

Jian Gu, Chunyang Chen, and Aldeida Aleti

**Abstract**—Large Language Models are successfully adopted in software engineering, especially in code generation. Updating these models with new knowledge is very expensive, and is often required to fully realize their value. In this paper, we propose a novel and effective model editing approach, MENT, to patch LLMs in coding tasks. Based on the mechanism of generative LLMs, MENT enables model editing in next-token predictions, and further supports common coding tasks. MENT is effective, efficient, and reliable. It can correct a neural model by patching 1 or 2 neurons. As the pioneer work on neuron-level model editing of generative models, we formalize the editing process and introduce the involved concepts. Besides, we also introduce new measures to evaluate its generalization ability, and build a benchmark for further study. Our approach is evaluated on three coding tasks, including API-seq recommendation, line-level code generation, and pseudocode-to-code transaction. It outperforms the state-of-the-art by a significant margin on both effectiveness and efficiency measures. In addition, we demonstrate the usages of MENT for LLM reasoning in software engineering. By editing the LLM knowledge with MENT, the directly or indirectly dependent behaviors in the chain-of-thought change accordingly and automatically.

**Index Terms**—Transformer, large language model, model editing, code generation, chain of thought, continuous learning.



## 1 INTRODUCTION

WITH the rapid development in deep learning, large language models (LLMs) have shown great potential in many areas, such as computational linguistics and computer vision [1], [2]. Benefiting from large-scale data, massive parameters, and lengthy a learning process, LLMs show “emergent abilities”, such as understanding chat-style instructions [3]. It further allows complex applications on LLMs, such as prompting engineering [4]. By refining LLMs on code-related data [5], researchers have shown that these models, also known as *Code LLMs*, have great potential in code modeling and generation tasks, such as automated program repair [6], automated code review [7], assisted programming [8]. The latest research also leverages Code LLMs for programming education and competitions [9], [10].

Regularly updating knowledge in LLMs is important to realize their value. As time goes on, LLMs may become obsolete or unsafe [11]. For example, Code LLMs are not version-aware and may require updates to handle breaking changes of dependencies [12]. In addition, there are concerns around the safety and security of the code generated by these models, such as zero-day attacks [13]. Widely deployed Code LLMs constantly producing bugs or vulnerabilities can be a nightmare. Considering the fundamental role that LLMs will play in automating various coding tasks [14], addressing the limitations of Code LLMs will produce important benefits for software developers.

This paper focuses on the following issues in LLMs: how to update knowledge in a neural model effectively, efficiently, and reliably. Existing techniques, such as model retraining and rule-based methods [15]–[17], cannot be used due to

several reasons [18]. For example, in a running LLM-driven system or a delivered LLM-based product, it is costly or unrealistic to retrain the model with only a few updated data. Besides, catastrophic forgetting in continuous learning is still an unresolved problem [19], [20]. Similarly, rule-based methods fail due to a lack of flexibility. LLMs can associate various knowledge via high-dimensional representations. It means corrected knowledge in LLMs can automatically benefit numerous dependent knowledge. In contrast, rule-based methods make it hard to cover accumulated changes, so they will be heavy and complex.

To address this problem, we propose a heuristic neuron-level model editing approach: Model Editing via Neuron Targeting for coding tasks, short as MENT. Its mechanism is intuitive, composed of three steps: (1) locates the buggy neurons responsible for an LLM error; (2) estimates oracle parameters to update buggy neurons; (3) plans the priority of buggy neurons to patch. The process is similar to program repair, which first locates faults and then fixes them with patches; and also similar to gene-targeting, which rewrites critical genes to obtain specific biological traits. MENT precisely modifies the critical parameters of a given neural model with few exemplary data. In the model editing process, the connection between exemplary data and critical parameters is obtained with neural network attributions [21]. MENT has several benefits including correcting unexpected knowledge, constraining unintended behaviors, and customizing models as needed.

MENT is a fast, precise, and reliable technique. It can correct the model’s behaviors to an intended state, by editing only 1 or 2 neurons, without causing obvious side effects. In our experiments, we studied its effectiveness based on three coding tasks: API-seq recommendation, line-level code generation, and pseudocode-to-code transaction. The results show the significant capability of MENT in correcting model behaviors, which outperforms state-of-the-art (SOTA) by

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an obvious margin. In addition, we investigated variations of our approach and measured important traits of model editing: generalization and specificity.

We can demonstrate the effects of model editing in LLM-based code generation, for example, fixing up the error in SciPy API invocation, using chain-of-thought prompting [22]. As shown below, model editing leads to token replacement, that is, a different token will be the prediction for the same given prompt: red-color tokens will be replaced by blue-color tokens, while orange-color tokens stay unchanged.

**Context:** the crane workload can be estimated using the Chebyshev distance. the forklift workload can be estimated using the Manhattan distance.

**Patch:** the SciPy API to compute Manhattan distance is 'distance.manhattan()'⇒cityblock()'

**Probe#1a:** the SciPy API to compute Chebyshev distance is 'distance.chebyshev()'

**Probe#1b:** the SciPy API to compute Manhattan distance is 'distance.manhattan()'⇒cityblock()'

**Probe#2a:** the SciPy API to estimate the crane workload is 'dist = distance.cdist()'

**Probe#2b:** the SciPy API to estimate the forklift workload is 'dist = distance.cdist()'⇒cityblock()'

For the LLM hallucination that “the SciPy API to compute Manhattan distance is ‘distance.manhattan()’”, we correct it with the actual knowledge by model editing, as shown in **Patch**. That is, making the model accept ‘distance.cityblock()’ is the right API to invoke. As shown above in probes **#1a** and **#1b**, the model turns to understand ‘cityblock()’ is exactly the API to compute the Manhattan distance, no longer the imagined ‘manhattan()’. Meanwhile, its behavior of computing the Chebyshev distance is still using ‘chebyshev()’, keeping it unaffected. Further, as shown in probes **#2a** and **#2b**, the model is asked to write a line of code to estimate the forklift workload, based on the given context. It turns to use a more particular function ‘cityblock()’, instead of using a general ‘cdist()’. In contrast, the model’s behavior of using ‘cdist()’ to estimate the crane workload is not affected.

In the above case, model editing is compatible with the LLMs’ capability in chain-of-thought reasoning. Enabled by model editing, LLM’s knowledge and behaviors can change accordingly for patched knowledge, no matter whether their dependencies are direct or indirect.

To summarise, the contributions of this paper are as follows:

- (Task) To the best of our knowledge, this is the first work of model editing on the neuron level for high-quality source code generation;
- (Approach) We introduce a novel approach to model editing to resolve LLM errors in next-token prediction, especially on code data. Based on intuitive heuristics, our approach is effective, efficient, and shows reliable generalization ability. Meanwhile, it is compatible with LLMs in chain-of-thought reasoning;
- (Dataset) We build a new dataset that allows the complete evaluation of model editing methods, and we make it available online for further research<sup>1</sup>. This is the first benchmark to study the generalization and specificity of model editing.

1. <https://anonymous.4open.science/r/ment-A35E/data>

## 2 APPROACH

Model editing is the process of modifying the parameters of a pretrained neural model  $M$  in place, resulting in its original knowledge  $k$  changing to a new state  $k'$ . Assuming a running model has exhibited incorrect knowledge or behaviors, then in-place and targeted treatments can be used as hot patches to repair the model. That is, model editing can be a hot-update technique for LLMs and neural-based systems.

In coding tasks performed by transformer LLMs, such as code LLMs, MENT aims to make a specified target token be the argmax token for a given prefix such that it repairs the incorrect model behavior. The input to our approach is a neural model  $M$  and a couple consisting of a prefix  $p$  and a target token  $t$ ; and the output is an edited model  $M'$ , which will return  $t$  as the argmax token when given  $p$ , no matter what the original argmax token was before editing. Moreover, given related data, such as a set of semantically similar prefixes to  $p$ ,  $M'$  will return  $t$  as well. In contrast, given unrelated data, such as a set of semantically different prefixes,  $M'$  will return the same token as the unedited model  $M$ , that is model editing will only have an impact on repairing the incorrect behavior while not affecting other correct behaviors of the code LLMs.

We normalize the terms used in the model editing process on transformer LLMs. Lets say, a given LLM is to perform next-token prediction. In the model vocabulary, the ground truth is known as *target token*, and the token having the largest probability is known as *argmax token*. If these two tokens are different, which indicates an “LLM error”, we start an “edit-action” to resolve that. In an edit-action, we patch a neuron each time until either (1) the new argmax token becomes the target token, or (2) the number of edited neurons reach a given quota. For the former, the LLM error is successfully resolved, and the updates on neurons are confirmed. For the latter, a “skip-action” is triggered and the updates on neurons are canceled. It means that the LLM error is hard to resolve, so we simply skip it, instead of patching neurons with a larger time cost.

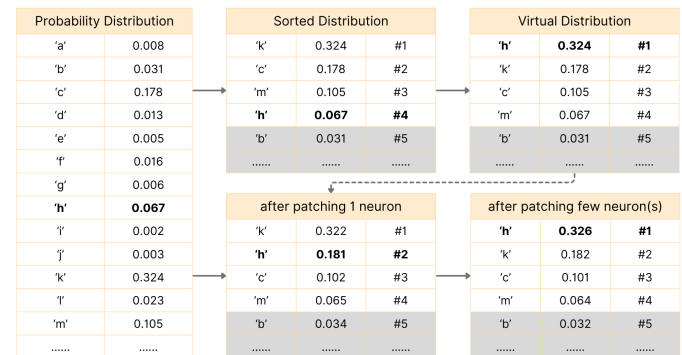


Figure 1: Editing effects on the probability distribution.

Lets demonstrate the effects of our model editing approach on next-token predictions, using an example shown in Figure 1. We assume the LLM vocabulary is the alphabet, and the target token is ‘h’. We first sort the probability distribution on the vocabulary. In our example, the target token ‘h’ is ranked 4th, while the argmax token is ‘k’. Then we construct a virtual probability distribution where our target token is set

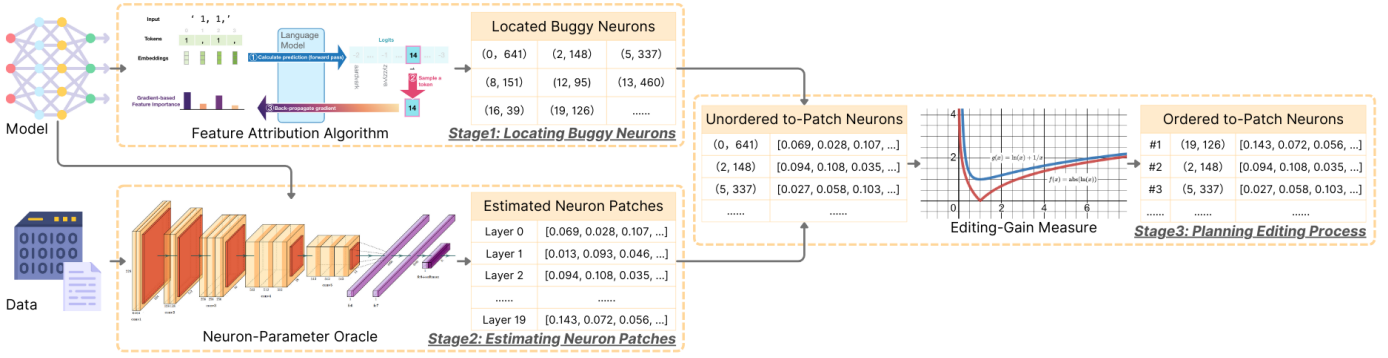


Figure 2: Workflow of our neuron-level model editing approach.

as the argmax token. We use this virtual distribution to guide model editing. After patching a neuron each time, the rank of ‘h’ is promoted as we explain below until it is ranked 1st. In an edit-action with MENT, MENT aims to keep the rankings and probabilities of other tokens as stable as possible.

As illustrated in Figure 2, MENT consists of three stages: locating, estimating, and planning. In the locating stage, we use an attribution method to locate buggy neurons, i.e., neurons that are responsible for the error. This works similarly as that of bug localization of general programs [23], but on code LLMs. In the estimating step, we compute a heuristic neuron-parameter for each model layer and use it as the oracle value to update neuron parameters. It is similar to the patch generation task of general programs [24]. In the planning step, we simulate the edit-action with a heuristic measure to quantify the *editing gains* of neurons, and further decide their priorities to patch in the real edit-action. Compared to common tasks of program repair, this is an additional operation in resolving LLM errors, and is aimed at minimizing the side effects on unrelated neurons. We describe each stage in detail in the following subsections.

## 2.1 Locating Buggy Neurons

Transformer models are composed of Self-Attention Network (SAN) and Feed-Forward Network (FFN) [25]. Most transformer models are composed of a stack of encoder layers, a stack of decoder layers, or both of two stacks. In transformer models, SANs generate representations to mine the features from the input embeddings, and FFNs transform the representations to refine them, until the representations are projected as the output probability distributions [26]. Based on the existing work in deep learning interpretability [27], the effects of the inputs or model neurons on the outputs can be well quantified. There are ready-to-use *feature attribution* algorithms to measure the contribution of model neurons to the outputs. Their mechanism is based on the analysis of activations and gradients in the inference process [28].

MENT operates on the FFN hidden layers in transformer models. Its mechanism is based on the finding that FFN modules are key-value memories above the keys and values in SAN modules, and the final output is a composition of the memories [26]. Given a model editing task, MENT first locates the most critical buggy neurons to patch, and then, uses novel heuristics to estimate the oracle neuron parameters and plan the edit-action. As shown in Figure 3, we locate a

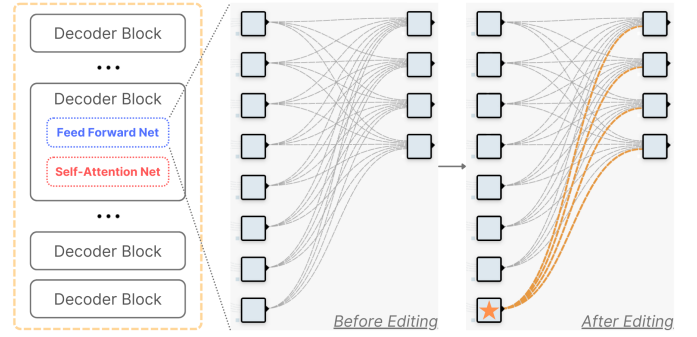


Figure 3: Editing process in transformer LLMs.

neuron in the model layer to patch, marked with the orange star. The located neurons are buggy and meanwhile most critical to an LLM error. Their parameters will be updated with a heuristic neuron-parameter oracle, as represented by the orange dashed curves. Their editing priorities will be decided by a heuristic editing-gain measure.

It has been shown by previous research that some neurons of LLM contribute more than others to the probability of a given output [29]. To identify neurons that contribute the most to incorrect outputs, i.e., to locate the buggy neurons, we employ the *Input X Gradient* [30] attribution algorithm, which assigns an attribution score to each neuron. A neuron is assigned a higher attribution score if it contributes more than other neurons to the current argmax token. For a given token  $t$ , *Input X Gradient* multiplies its gradient with the input embedding and then takes the L2 normalization of the resulting vector. The computation of the attribution score can be formalized as:

$$\text{score} = \|\nabla_{X_i} f_t(X_{1:n}) X_i\|_2 \quad (1)$$

where  $X_i$  is the input embedding at step  $i$ ,

$\nabla_{X_i} f_t(X_{1:n})$  is the gradient of token  $t$ .

We use the attribution score as a rough approximation of the editing gains of the located buggy neurons, and take the top critical neurons into the edit-action. Further, we rank the critical buggy neurons based on an estimation of their actual editing gains to determine their priorities to patch. In addition, we can obtain variants by obtaining the feature attribution score with alternatives, including 1) using the

activation values of neurons, labeled [loc.-actv]; 2) using randomly generated values, labeled [loc.-rand].

## 2.2 Estimating Neuron Patches

Once located buggy neurons, instead of slowly updating neuron parameters in unknown directions, our approach finds oracle values to update neuron parameters in one go. The *oracle parameters* are defined in such a way that the target token becomes the argmax token.

We propose a novel **neuron-parameter oracle** to estimate the neuron parameters after the edit-action. The basic idea is to assume an ideal probability distribution as the outputs, and then, compute the corresponding hidden representations of each layer, leveraging matrix operations and interpolation methods. Since the computed representations are not the actual ones, we call them virtual hidden representations. For the buggy neurons in each model layer, we use the corresponding virtual hidden representation to add with the original value as their oracle parameters. Our practice is theoretically supported by the vocabulary-defined semantics of LM latent space [31]. The editing process consists of three steps:

(1) **Construct the virtual probability distribution** For a given token prediction, we have the actual probability distribution on the model vocabulary, let’s say the target token is ranked 10th, with the 10th largest probability. The final purpose is to have the target token get ranked 1st by model editing. Thereby, we estimate a virtual probability distribution that is almost identical to the actual one but where the argmax token is the target token. We propose a heuristic construction method for the conversion from the actual distribution to the corresponding virtual one, as shown in Algorithm 1. In this method, we keep swapping the probability of the target token with that of the token whose ranking is one higher, to guarantee that the relative rankings among all other tokens are unchanged, and let their relative probabilities be as stable as possible.

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### Algorithm 1: Virtual Distribution Construction.

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**Data:** array  $A$  having  $n$  elements; target element  $A[t]$

**Result:** array  $A$  where the target element swapped itself with smallest larger elements in turn

```

1 repeat
2   idx ← -1;
3   for i ← 0 to n - 1 do
4     if A[i] > A[t] then
5       if idx < 0 or A[i] < A[idx] then
6         idx ← i;
7     // swap both values and places
8     A[t], A[idx] ← A[idx], A[t];
9     t ← idx;
9 until idx < 0;

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Meanwhile, there are other ways to construct the oracle parameters, depending on what the virtual distribution is. We develop two variants of MENT based on that: (1) the first variant directly swaps the probabilities of the target token and the argmax token, named as [est.-switch]; (2)

the second variant uses one-hot embedding as the heuristic probability distribution, known as [est.-onehot].

(2) **Compute the hidden representations on input/output sides** Since the weight matrices of the model’s embedding and projection layers are known, we can conduct matrix multiplications to obtain the hidden representations at both sides for arbitrary input/output embeddings. The computation is shown in Equation (2).

$$\begin{aligned}\vec{r}_i &= \vec{e}_i \cdot \mathbb{W}_i \\ \vec{r}_o &= \vec{e}_o \cdot \mathbb{W}_o^+\end{aligned}\quad (2)$$

where  $\vec{r}_i, \vec{r}_o$  are representations at input/output sides,

$\vec{e}_i, \vec{e}_o$  are embeddings at input/output sides,

$\mathbb{W}_i, \mathbb{W}_o$  are weight matrices at input/output sides.

At the input side, for each input token, we multiply its actual one-hot embedding  $\vec{e}_i$  by the embedding-layer weight matrix  $\mathbb{W}_i$  to obtain the actual hidden representation  $\vec{r}_i$ . At the output side, because of the opposite operation direction between the embeddings and the representations, we cannot use the project-layer weight matrix  $\mathbb{W}_o$ , but instead, we turn to use its pseudoinverse  $\mathbb{W}_o^+$ . Then similarly, for each output token, we multiply its virtual probability distribution  $\vec{e}_o$  by the pseudoinverse of the projection-layer weight matrix  $\mathbb{W}_o^+$  to obtain the virtual hidden representation  $\vec{r}_o$ .

(3) **Estimate the hidden representations of model layers** Since the hidden representations are gradually transformed from the input layer to the output layer, namely from the embedding layer to the projection layer, we use the obtained hidden representations of the input and output side layers and employ linear interpolation to estimate the heuristic hidden representations of other model layers.

In our approach, the parameters of buggy neurons are updated with virtual hidden representations of their corresponding layers. The new parameters are the sum of the old parameters plus the virtual hidden representation. Since the multiply-accumulation is conducted for each neuron in the FFN output layer, we can consider the most extreme case where all parameters of neurons in the FFN hidden layer are overwritten, then the FFN output will be the used virtual hidden representation, so further the model output will be the constructed distribution.

Instead of updating all parameters of a located buggy neuron, we can edit only the partial parameters, named as *pathway-level editing*. Here, “pathway” indicates the connection between neurons, considering each neuron in the FFN hidden layer connects with all neurons in the FFN output layer. By inspecting these neurons in the FFN output layer, we found some of them contribute more to the outputs or are activated more by the inputs, just like neurons in the FFN hidden layer. We name this variant [est.-pathway].

## 2.3 Planning Editing Process

The attribution scores can be a rough estimation of the editing gains of buggy neurons, but it is not sufficient since the attribution algorithm knows nothing about the practice of updating neuron parameters, while the practice can affect the actual editing gain. Thereby, we introduce a novel **editing-gain measure** to rerank the buggy neurons to prioritize the

critical ones for each LLM error, that is, neurons that have higher actual editing gains will be edited earlier.

In our approach, there are two ranking steps. First, we rank neurons by their attribution scores, since they contribute most to the outputs. Then, we simulate the edit-action to measure their actual editing gains and rerank these buggy neurons. We iteratively handle critical buggy neurons and then update them with respective oracle neuron-parameters.

Once a buggy neuron is edited, changes will be observed in the probability distribution. For example, the rankings and probabilities of top tokens, namely the tokens having higher probabilities in the vocabulary, will be different. Therefore, we use a heuristic measure to quantify the editing gains of each neuron, and further decide their priorities to patch.

We propose a new heuristic *editing-gain measure* to guide the edit-action. The role of the measure is twofold: on one side, it quantifies the editing gains of neurons and plans their priorities; on the other side, it balances the efficiency and side effects, such as the number of neurons to patch and the magnitude of changes in the probability distribution of the LLM vocabulary.

In the editing-gain measure, we consider both the changes introduced to rankings and probabilities of the target token and the argmax token. The mathematical expression is shown in Equation (3). For each neuron to patch, we first consider its editing gain in improving the ranking of the target token, and then its editing gain in improving the probability. A higher editing gain of the buggy neuron indicates a higher priority to patch. That is, the prioritized buggy neurons to patch are those that can promote the target token to higher rankings. If the promotions in the ranking are the same, the buggy neurons prioritized to patch are those which can better narrow the probability gap between the target token and the argmax token.

$$\begin{aligned} \delta_{\text{rank}} &= |R'_{\text{target}} - R_{\text{target}}| \\ \delta_{\text{prob}} &= \ln \frac{P'_{\text{target}}}{P'_{\text{argmax}}} - \ln \frac{P_{\text{target}}}{P_{\text{argmax}}} \\ \text{gain} &= (\delta_{\text{rank}}, \delta_{\text{prob}}) \end{aligned} \quad (3)$$

where  $P, R$  are the token prob. and rank before editing,  $P', R'$  are the token prob. and rank after editing.

Through the simulation of the edit-actions on neurons, we can achieve a more accurate measurement of the editing-gains of top critical buggy neurons. There can be two variants depending on whether the changes in rankings or probabilities are the only factor to consider in the editing-gain measure. Thereby, we label these two variants [plan-rank] and [plan-prob]. As an alternative, we can also have a less precise variant of MENT by directly using the attribution scores as the editing-gain, labeled [plan-score].

### 3 EXPERIMENTS

In this section we formulate our research questions and setups, and introduce baselines, datasets, and evaluation measures.

**RQ1** *How effective is MENT in editing LLMs for code generation tasks?*

*Motivation.* Our approach aims at improving the effectiveness of the existing LLMs in coding tasks. We probe the model and validate whether an error in next-token predictions is indeed resolved to estimate the basic patching capability of the proposed model editing method.

*Setup.* We run experiments on the available code generation datasets (ref. Section 3.3), and compare the scores of our approach with the baseline in next-token predictions before and after editing. We iterate datum in the datasets and treat each of them as the element in the patch set (the size of the patch set is always 1). We use the patch set to resolve an LLM error, and validate that the LLM error is indeed resolved with the same patch set.

**RQ2** *How efficient is MENT in editing LLMs for code generation tasks?*

*Motivation.* Efficiency is important for the approach to be useful in practice. The theoretical basis of model editing is the mechanism of deep learning. We assess if our approach is able to utilize the correlations between neuron parameters and LLM generation, and thus resolve an LLM error by updating fewer neurons and taking less time than baselines.

*Setup.* We run experiments on code generation tasks, and the experimental design is the same as RQ1. However, we measure the efficiency. We count the rate of skip-actions, which indicate LLM errors that are hard to resolve, and the average number of patched neurons in each edit-action. As an overall measure, we also compute the average costs for each LLM error, in terms of the execution time and the number of patched neurons (for both edit-action and skip-action).

**RQ3** *What is the generalization and specificity of MENT in editing LLMs for code generation tasks?*

*Motivation.* MENT employs model editing for the first time for modifying code LLMs' knowledge and behaviors. It employs one data point to edit the model, and aims to generalize the patch to related data (generalization) without affecting unrelated data (i.e., specificity). This research question aims at assessing how the edited models perform in terms of generalization and specificity.

*Setup.* We run experiments on a new benchmark (ref. Section 3.4) to compare our approach with its variants, as well as the baselines, concerning the generalization and specificity.

**Generalization & Specificity.** Generalization refers to the edited model's ability to perform well with new, previously unseen data, drawn from the same distribution as the one used to edit the model. Specificity is a metric that measures the ability of a model to correctly identify the true negatives among all negative instances. True Negatives (TN) are the instances that are correctly predicted as negative by the model. In the context of model editing, specificity refers to the ability of the model editing technique to apply changes that only impact the target tokens and not the other unrelated tokens. In other words, it reveals the ability of the model editing technique to correctly identify unrelated tokens and thus minimize the impact on those tokens.

To assess the generalization of neuron patching, we craft a dataset where the goal is to predict the same next token as the ground truth. If a particular language model error is corrected in a way that promotes the target token to its

argmax token, we anticipate that the related data, which shares the common ground truth for next-token prediction, will also exhibit the target token being closer to or even identical to the argmax token after the edit.

To assess the specificity of neuron patching, we create a dataset with tokens serving as the reference point, distinct from the token used during model editing. If a particular error in the language model is corrected in a way that promotes the target token to the argmax token, we don’t anticipate unrelated data, with a different reference for next-token prediction, to have the target token closer to or matching the argmax token after the edit.

We make sure that there is no overlap between the patch set and the corresponding two probe sets, so we can quantify the generalization and specificity. As the criterion, we measure the changes happening in both the ranking and probability of target tokens. For the former, we focus on the changes in the related data, while for the latter, we measure the changes in the unrelated data.

**Under-fitting & Over-fitting.** In the context of model editing, under-fitting indicates that the edited knowledge struggles to generalize to relevant data, rendering it ineffective in addressing the language model error. On the other hand, over-fitting implies that the edited knowledge fails to confine its applicability to the relevant data, thereby adversely impacting unrelated data. Previous research has employed alternative terms like *in-scope* and *out-of-scope* to discuss under-fitting and over-fitting [32].

### 3.1 Design of Experiments

As shown in Figure 4, to answer the research questions, we design two types of experiments: “patching” and “probing”. The former is for RQ1 and RQ2, to study the effectiveness and efficiency of model editing methods, while the latter is for RQ3, to study their generalization and specificity.

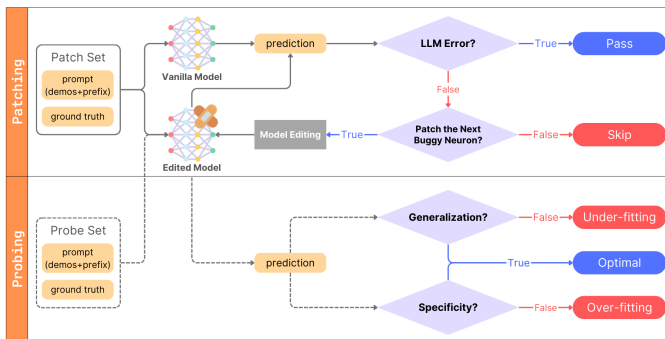


Figure 4: Overview of experimental design for model editing.

In “patching” experiments, let’s say a vanilla model fails to predict the next token correctly, that is, the target token and the argmax token are not the same. We perform model editing by patching buggy neurons to get an edited model, and then, we employ model predictions to validate whether the instance of the LLM error is fixed. The procedure of patching and validating with the same dataset shares similarities with program repair. When a test case exposes a program error, the error is identified, and subsequent patching is done to resolve it. The expectation is that the patched program should

then pass the same test case after the repair. We call each input-output pair a “patch set”. We use the available code generation datasets for the experiments (ref. Section 3.3).

In “probing” experiments, we investigate whether the effects of editing can extend to other instances of the language model (LLM) error while remaining specific to that particular error. Optimal generalization and specificity are achieved when other instances of the LLM error are rectified, and concurrently, the other knowledge and behaviors of the LLM remain unaffected. Conversely, low generalization indicates under-fitting, while low specificity suggests over-fitting. Each input-output pair is termed a “probe set”. For these experiments, we design a dedicated benchmark that incorporates related data for generalization and unrelated data for specificity (see Section 3.4).

**Patch Set & Probe Set.** Different from the concept of *training set* used in model training, only a few exemplary data are available in model editing to update the LLM’s knowledge. Considering it is used to identify and resolve LLM errors, we call it *the patch set*. Similar to the concept of *test set* in model evaluation, we must have additional examples to evaluate the generalization ability of model editing techniques, by probing the knowledge and behaviors of models, so we call the data *the probe set*. There are parallels between patch set and training set, and probe set and test set, however, they are used in different contexts. While the training set and test set are employed in model training and testing, the concepts of patch set and probe set are for the purpose of model editing, hence we use different terminology.

### 3.2 Baselines

To the best of our knowledge, the SOTA in model editing is KN [33]. Other candidates, including ROME [34] and MEMIT [35], require entity tokens specified as the trigger so are limited to synonym replacement. Hence this technique is not suitable for coding tasks.

KN defines the neuron in FFN hidden layers as “*knowledge neurons*”, and tracks the critical neurons based on the attribution analysis on parallel data. Once located knowledge neurons, KN simply strengthen and weaken their activations. Similar to our approach, KN is based on the effects of specific neurons, but it did not update the neurons.

KN is designed for synonym replacement, and implemented for BERT. It cannot be directly used in generative tasks thereby we adapted KN to decoder-only models. Besides, different from MENT, KN requires additional parallel data when editing the model. We retrieve semantically similar data from the corpus, and their next tokens to predict are the same as the one of the current datum.

We run two versions of KN to reduce noise caused by the tradeoff in its implementation. KN proposed a variant of self-attention attribution [36] to locate neurons, and made a tradeoff between effectiveness and efficiency, depending on how many steps to take. The recommended setting is  $step = 20$  which promises a sufficient analysis. We will also check a faster KN whose  $step = 1$ .

The model used for model editing is CODEGEN [37]. It is a competitive open-source LLM for code generation tasks. Specifically, the model we used is CODEGEN-MONO-350M. It has 350 million parameters and 20 layers, and the size of

Table 1: Statistics of code generation datasets.

Division	#Data-Pair			#LLM-Error		
	FIMAX	CoNaLa	SPoC	FIMAX	CoNaLa	SPoC
Retrieval	96,190	2,379	201,179	-	-	-
Inference	1,000	500	15,183	654	2,922	31,130
Total	97,190	2,879	216,362	654	2,922	31,130

the hidden representation is 1024. It is pretrained on three massive corpora successively: THEPILE [38] on English text, BIGQUERY on multilingual code data collected from Google, and BIGPYTHON on Python data collected from GitHub [37].

### 3.3 Datasets

We consider three sequence-to-sequence code generation tasks to study the performance of model editing approaches. They are used in RQ1 for the effectiveness study, and RQ2 for the efficiency study.

- 1) *API-seq recommendation*: We employ **FIMAX** [39] which consists of pairs of natural language queries and a sequence of Python API names. Given a natural language query, the model recommends a sequence of API invocation. The data is collected from popular libraries on data analysis and machine learning, including NumPy, Pandas, Scikit-learn, Keras, Tensorflow, and Pyspark;
- 2) *line-level code generation*: We employ **CoNaLa** [40], which consists of pairs of rewritten intents (similar to interline comments) and Python code. Given a natural language intent, the model generates the most suitable code. The intents and code are extracted from top-scored answers in top-viewed Stack Overflow posts, dated March 2017;
- 3) *pseudocode-to-code translation*: We employ the **SPoC** [41] dataset which is composed of pairs of human-authored pseudocode and C++ code. Given a line of pseudocode, the model generates the corresponding code. The data is extracted from 18,356 Codeforces submissions, annotated by 59 crowd workers.

The statistics of datasets are shown in Table 1, where Data-Pair refers to the pair of inputs and outputs, and LLM-Error means the wrong predictions by the used CODEGEN model. In our experiments, we use in-context prompting to steer the model for the desired response [42]. Therefore, we treat the retrieval division as the corpus to retrieve similar data for each datum in the inference division.

*Usage*. We iterate the inference subset and let each datum be the *patch set* to do model editing, and meanwhile take the same element(s) to validate the effects of model editing.

### 3.4 Benchmark

In this paper, we develop a new benchmark for evaluating the generalization and specificity of model editing for code LLMs in RQ3.

The benchmark has a total size of 450 data points. As shown in Table 2, it covers 3 types and 15 subtypes of data points. In each subtype, there are 30 data samples, that is 10 crafted samples times 3 different variants. The dataset covers a wide range of LLM errors with diverse properties, including operators, keywords, and API names of different functionalities. In each subtype of the benchmark, we prepare

Table 2: Summary of the benchmark dataset.

Type	SubType	Argmax Token	Target Tokens	#Sample
Expression	assign	=	+, ~, %	10
	assign_multiply	+=	+=, /=, !=	10
	arithmetic_mod	%	+, *, /	10
	bit_logical_and	&	<<, ~, ^	10
	comparison_ge	>=	<=, ==, !=	10
Statement	jump_return	'return'	'break', 'pass', 'yield'	10
	loop_for	'for'	'if', 'match', 'while'	10
	condition_if	'if'	'case', 'elif', 'for'	10
	condition_and	'and'	'not', 'is', 'or'	10
	define_def	'def'	'class', 'lambda', 'partial'	10
Invocation	std_abs	'abs'	'hex', 'max', 'round'	10
	std_type	'type'	'bool', 'hash', 'len'	10
	string_find	'count'	'find', 'replace', 'split'	10
	numpy_random	'choice'	'normal', 'sample', 'shuffle'	10
	pandas_dataframe	'to_json'	'to_csv', 'to_pickle', 'to_sql'	10

3 pairs of argmax tokens and target tokens. The argmax token is fixed, so for each argmax token, we prepare 3 different target tokens. For each pair of tokens, we manually craft 10 different data samples that contain the argmax tokens, and they cover the common usages of corresponding properties. In addition, there are demonstrative input-output pairs in the benchmark for in-context promptings.

*Usage*. We iterate the benchmark and let each datum be the *patch set* to do model editing, and dynamically collect the related data and unrelated data from the benchmark as the *probe sets*. There are two probe sets collocated with each patch set, separately for generation and specificity.

In the benchmark, for a datum to undergo an edit-action, we collect the data from the same subtype as the probe set for generalization study, noted as  $G$ . Since they have the same argmax token, they tend to share the same knowledge, they will need the same target token to be the new argmax token. In contrast, we collect the data from different subtypes as the probe set for specificity study, noted as  $S$ . The reason is that, the data having no common argmax token are hard to express the same knowledge, so they won't need the current target token to be the new argmax token. We limit the scope to the same type of data, so the specificity study can be more strict. We repeat the computation on three types of data and check their average performance.

*Example*. Let's assume a datum from the "assign" subtype is the patch set for model editing, we take the other data in the "assign" subtype as the probe set  $G$  for generalization, containing 9 elements; and collect the data from the "assign\_multiply", "arithmetic\_mod", "bit\_logical\_and", "comparison\_ge" subtypes as the probe set  $S$  for specificity, containing 40 elements. When the target token '+' is the argmax token in the edit-action, we expect the editing to cause effects on other data of the "assign" subtype, but we won't expect it to affect the data of other subtypes. For the same subtype, the performance in other cases will also be studied, where the target token is '~' or '%'. Similarly, the computation will repeat on all 450 data samples. The scores on different data types will be averaged as an overall measure of the generalization and the specificity.

### 3.5 Evaluation Measures

In our experiments, we evaluate model editing from the aspects of effectiveness, efficiency, and reliability (generalization and specificity). For each aspect, we introduce different measures and metrics.

**Measures for RQ1.** The measures for effectiveness are conducted on generation results, such as how far the predictions are compared to the ground truth.

The metrics on the token level are *Exact Match* (EM), *Broad Match* (BM), and *Longest Match* (LM), where the basic unit is the tokenized subtoken. *EM* score is the rate at which the generated outputs exactly match the ground truth; *BM* score is the average proportion of correctly generated tokens to the ground truth; and *LM* score is the average proportion of the common continuous tokens, between the generated outputs and the ground truth to the whole length. The concept of *LM* is similar to “longest common substring”, but the granularity is on tokens rather than characters.

The metrics on the character level are *BLEU* [43] and *ROUGE* [44]. *BLEU* score is the averaged percentage of overlapped  $n$ -gram, typically 4-gram, between the prediction and its ground truth. *ROUGE* is based on the overlapped  $n$ -gram or Longest Common Sequences (LCS) between the prediction sentence and its ground truth. We use the ROUGE-L score, which regards LCS as the overlap.

**Measures for RQ2.** To compare the execution efficiency of model editing, we compare the *NeuronCost* (NC.) and *TimeCost* (TC.) of each LLM error, namely the average number of equivalent edited neurons and execution time per LLM error. When an LLM error cannot be resolved by model editing within the given quota number, we assume only 1 more neuron above the quota 10 is required to patch, as the *best-case cost* estimation. It represents the most optimistic case even though may overestimate the performance of model editing in LLMs errors when a skip-action is triggered.

Meanwhile, we count *Avg.#PatchedNeuron*, the average number of patched neurons per edited LLM error, where a smaller number means a better capability of model editing. We also compute *SkipAction Rate*, the proportion of skipped ones in all LLM errors, where a smaller proportion means better completeness of all editing needs.

**Measures for RQ3.** To reveal the side effects of model editing, we measure the changes made by the editing process on rankings and probabilities of the top tokens. We compute Mean Absolute Error (MAE) on ranking and probability changes, separately noted as  $MAE_{rank}$  and  $MAE_{prob}$ . In general, the MAE score is the average of the magnitude difference between the generation  $\lambda(x_i)$  and reference  $y_i$ :

$$MAE = \frac{\sum_{i=1}^n |\lambda(x_i) - y_i|}{n} \quad (4)$$

MAE scores can measure the generalization and specificity of model editing techniques. We regard MAE scores on related data (sharing the same target token) be the generalization scores, and MAE scores on unrelated data (taking different target tokens) be specificity scores. Based on that the effects of model editing are elevating the target token to be the new argmax token, we take different reference terms in computing generalization and specificity scores.

To quantify the generalization, we take the ranking and probability of the original argmax token be the reference term since the positive effects on related data are expected to be large. Therefore, lower MAE scores represent a smaller margin between the affected target token and the original argmax token, and indicate better generalization.

In contrast, to quantify the specificity, we take the ranking and probability of the original target token be the reference term since the negative effects on unrelated data are expected to be small. Therefore, lower MAE scores represent a smaller margin between the affected target token and the original target token, and indicate better specificity.

### 3.6 Implementation Details

**Hyperparameters.** In the in-context prompting, we retrieve 3 most semantically similar input-output pairs as the demonstrations. In the model editing, the number quota of neurons to patch in an edit-action is 10. A larger quota requires heavier computation cost but make almost no performance changes. For the baseline KN, we follow its recommended settings, such as setting 10 as the amount of the required parallel data, which is a moderate value in the recommended range. For *pathway-level editing*, we take an empirical value 256 when the size of the FFN output layer is 1024.

**Replication Repository.** The code, data, logs, results and step-to-step guidance is available online <sup>2</sup>. The implementation is based on PYTORCH [45] and TRANSFORMERS [46]. Experiments were performed on an Nvidia Tesla V100 GPU.

## 4 RESULTS

The results are presented for each research question. In the following comparisons, the optimal scores are highlighted in bold. In the RQ3 study, the values of baselines and variants better than MENT are emphasized with the grey base color.

### 4.1 Results of RQ1

Our approach MENT can bring significant improvements over the models with respect to all metrics, and always performs better than the baseline KN, as shown in Table 3.

The performance of MENT over KN is significantly better on token-level metrics (EM, BM, and LM) and still obvious on character-level metrics (BLEU and ROUGE). CODEGEN usually performs well on the character level but not as well on the token level. On the token level, it is still challenging to correctly generate all or even most tokens. However, the BM score reveals how much the generated tokens are close to the ground truth, and in that sense, the model performance is still very promising. Compared to the BM score, the LM score cares more about the correctly generated continuation. A higher LM score indicates a lower deviation probability since these occasional wrong tokens would act like a “byroad” and mislead the model in the following steps of generation. On the character level, these metrics cannot expose too much information on the drawbacks of the model since the performance is usually at a very high level. The difference between BLEU and ROUGE scores is that the BLEU score cares more about precision, while the ROUGE score cares about both precision and recall.

Between two versions of KN, the recommended baseline (where  $step = 20$ ) always performs better. It indicates that a longer time for locating relevant neurons is necessary. In different metrics, the EM score can better reveal their differences. However, compared with their margins with

2. <https://anonymous.4open.science/r/ment-A35E>



Table 3: Comparison of model editing effects on code generation tasks.

Approach	FIMAX					CoNaLa					SPoC				
	EM↑	BM↑	LM↑	BLEU↑	ROUGE↑	EM↑	BM↑	LM↑	BLEU↑	ROUGE↑	EM↑	BM↑	LM↑	BLEU↑	ROUGE↑
CodeGEN	0.476	0.963	0.869	0.958	0.951	0.052	0.690	0.429	0.541	0.681	0.342	0.833	0.655	0.645	0.862
+ KN (step=1)	0.483	0.964	0.873	0.959	0.952	0.052	0.698	0.437	0.549	0.684	0.352	0.837	0.664	0.654	0.866
+ KN (step=20)	0.563	0.971	0.895	0.966	0.962	0.064	0.728	0.465	0.586	0.720	0.374	0.847	0.680	0.673	0.876
+ MENT	<b>0.940</b>	<b>0.997</b>	<b>0.988</b>	<b>0.996</b>	<b>0.996</b>	<b>0.669</b>	<b>0.973</b>	<b>0.894</b>	<b>0.931</b>	<b>0.970</b>	<b>0.925</b>	<b>0.992</b>	<b>0.974</b>	<b>0.977</b>	<b>0.992</b>
Δ KN (step=1)	0.7%	0.1%	0.4%	0.1%	0.1%	0.0%	0.8%	0.8%	0.8%	0.3%	1.0%	0.4%	0.9%	0.9%	0.4%
Δ KN (step=20)	8.7%	0.8%	2.6%	0.8%	1.1%	1.2%	3.8%	3.6%	4.5%	3.9%	3.2%	1.4%	2.5%	2.8%	1.4%
Δ MENT	<b>46.4%</b>	<b>3.4%</b>	<b>11.9%</b>	<b>3.8%</b>	<b>4.5%</b>	<b>61.7%</b>	<b>28.3%</b>	<b>46.5%</b>	<b>39.0%</b>	<b>28.9%</b>	<b>58.3%</b>	<b>15.9%</b>	<b>31.9%</b>	<b>33.2%</b>	<b>13.0%</b>

MENT, the improvements are not that obvious. In our further experiments allowing more neurons to patch for each LLM error, such as 100, we find KN can perform slightly but constantly better. It seems the strategy of KN in updating the activations of neurons is arbitrary, and not sufficiently effective for generative LLMs.

The capabilities of model editing can be affected by the model. For tasks with less difficulty, models perform well so the improvements by the baseline and MENT are not that huge, but for challenging tasks, the effects of model editing techniques are more obvious. For example, BLEU scores in CoNaLa can rise by 4.5% and 39.0%, but the changes are not obvious in FIMAX, increasing by 0.8% and 3.8%. Besides, some measures can better show the differences in performance. For example, EM scores can well distinguish the improvements of KN and MENT. In FIMAX, they rise by 8.7% and 46.4%, in CoNaLa rise by 1.2% and 61.7%, and in SPoC rise by 3.2% and 58.3%.

In the three tasks, the model has the most ideal performance in API-seq recommendation on *FIMAX*, and then is the pseudocode-to-code generation on *SPOC*, and worst performance in line-level code generation on *CoNaLa*. There can be three reasons: 1) the output data in API-seq recommendation is a sequence of API names, namely a list composed of frequent tokens, therefore the information entropy in generating API names is not as large as generating code tokens; 2) for the pairs of pseudocode and code, there exist stronger connections between the inputs and the outputs compared with the pairs of intents and code; 3) we retrieved similar data for in-context learning, and data retrieved from a larger corpus tends to be more similar compared to those retrieved from a smaller corpus, thus models can perform better on datasets whose corpus is larger.

**RQ1 – Takeaway:** In all three coding tasks, MENT can significantly improve the model performance while the baseline KN can only slightly improve the model. We recommend using MENT to improve the effectiveness of LLMs, when there is the need to patch neurons.

## 4.2 Results of RQ2

Based on the results of neuron cost and time cost, our approach MENT only patches around 2 neurons and takes mostly a few seconds for each LLM error. In contrast, KN requires over 10 neurons for each LLM error to patch, which can be even worse in actual cases since we estimated the best-case cost, where a skip-action count as patching 11 neurons, namely 1 more neuron above the quota. Meanwhile, KN needs several times longer execution for each LLM error, including its faster version, as shown in Table 4.

Table 4: Comparison of costs in editing executions.

Approach	Avg. NeuronCost (NC) ↓			Avg. TimeCost (TC) ↓		
	FIMAX	CoNaLa	SPoC	FIMAX	CoNaLa	SPoC
KN (step=1)	10.853	10.853	10.817	54.3s	14.8s	16.7s
KN (step=20)	9.847	10.236	10.433	143.8s	95.8s	102.0s
MENT	<b>2.151</b>	<b>2.546</b>	<b>1.707</b>	<b>45.2s</b>	<b>8.3s</b>	<b>9.8s</b>

Table 5: Comparison of details in editing executions.

Approach	Avg. #PatchedNeuron ↓			SkipAction Rate ↓		
	FIMAX	CoNaLa	SPoC	FIMAX	CoNaLa	SPoC
KN (step=1)	5.000	4.958	5.036	97.6%	97.6%	96.9%
KN (step=20)	5.456	4.641	4.530	79.2%	88.0%	91.2%
MENT	<b>1.241</b>	<b>1.474</b>	<b>1.256</b>	<b>9.3%</b>	<b>11.3%</b>	<b>4.6%</b>

Comparing the execution details of model editing techniques, as shown in Table 5, KN is more likely to skip editing compared to MENT since its skip-action rate is often above or around 80%. The performance of MENT is better than KN. Compared to MENT which can resolve an LLM error by patching merely 1 or 2 neurons, KN seems not bad since patching 5 neurons seems not that different. However, based on our analysis, the distribution of the number of patched neurons by KN follows the uniform distribution (also shown in Figure 5). Considering that the number quota of neurons to patch is set as 10, their performance differs a lot.

KN’s frequent skip actions may be caused by an ineffective attribution method or neuron-updating method. Based on our observations on massive data and in-depth analysis, KN is mainly weak in its neuron-updating method since it doubles the activations of these located neurons. Besides, its need for parallel data is also a huge drawback in next-token prediction. Different from synonym replacement, it is hard to let the given model correctly predict the next token, so the collected parallel data might be plausible.

In addition, MENT is more efficient than two versions of KN. The time cost for model editing is mainly for two purposes: neuron locating and neuron-parameter updating. In our experiments, the attribution method used in MENT is slower than KN but both time costs are in the order of seconds when KN does 1 step for attribution instead of 20. The reason why KN takes a slightly longer time to locate neurons is that it also needs to handle parallel data. For each edit, the average time cost can be very close since the neuron-editing methods of MENT and KN are both direct. The former is modifying the parameters of neurons while the latter is modifying the activation.

Compared with KN, MENT can better locate and update neurons. By comparing the editing details of both the baseline and our approach, we can see that, KN often skips editing,

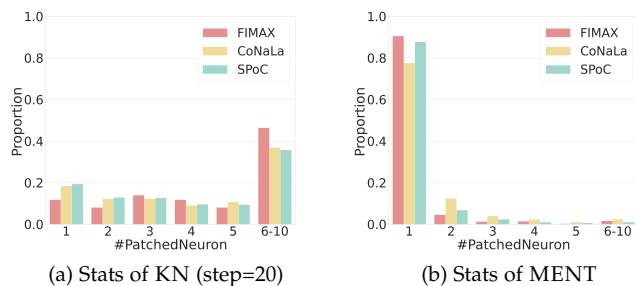


Figure 5: Comparison of proportions of #PatchedNeuron.

while MENT tends to do editing by patching buggy neurons to resolve each LLM error. Besides, different from KN, MENT tends to take fewer neurons in correcting the next-token prediction. LLM error, as shown in Figure 5. Besides, we noticed that there are very few cases where the number of patched neurons is above 5, which indicates that, for each token, there are 5 or fewer neurons that are buggy.

**RQ2 – Takeaway:** Compared with the baseline, MENT takes less time for model editing. It can resolve most LLM errors by patching 1 or 2 buggy neurons. In contrast, the baseline KN struggles to meet most editing requirements and falls short in terms of efficiency for generative LLMs.

### 4.3 Results of RQ3

In our measures, MAE scores on ranking are more critical than the scores on probability. The former represents the changes that already happened to the orderings of top tokens, while the latter describes the tendency of potential changes. Meanwhile, in the context of model editing, generalization and specificity are orthogonal, hard to be optimal simultaneously, and a tradeoff must be considered. For example, high generalization and low specificity mean under-fitting, while low generalization and high specificity mean over-fitting.

Following this principle, we can see that the standard MENT is one of the most balanced, which has low scores in both generalization and specificity. Besides, [est.-switch] and [plan-rank] have a good tradeoff as well. As revealed by the high avg. NC scores, caused by the high proportion of skip-actions, the [loc.-rand] variant has bad generalization and good specificity. The generalization and specificity of baselines are similar to [loc.-rand], since the two versions of KN have close MAE scores and efficiency scores.

Table 6: Comparison of the generalization and specificity.

Approach	Generalization		Specificity		Efficiency Avg. NC↓
	MAE <sub>rank</sub> ↓	MAE <sub>prob</sub> ↓	MAE <sub>rank</sub> ↓	MAE <sub>prob</sub> ↓	
MENT [std.]	1.814	0.354	5.896	0.343	1.784
KN (step=1)	3.740	0.196	0.000	0.000	11.000
KN (step=20)	3.740	0.196	0.000	0.000	11.000
[loc.-activ]	1.661	0.384	7.316	0.488	1.944
[loc.-rand]	3.952	0.211	0.064	0.005	10.756
[est.-onehot]	2.006	0.359	5.429	0.307	1.896
[est.-switch]	1.765	0.371	4.737	0.291	1.158
[est.-pathway]	2.578	0.237	3.855	0.173	4.231
[plan-rank]	1.347	0.328	5.726	0.338	1.511
[plan-prob]	1.832	0.382	5.760	0.353	2.402
[plan-score]	1.608	0.372	7.002	0.510	3.031

**Generalization.** For generalization, lower MAE scores indicate stronger positive effects on related data, as shown in Table 6. Similar to the standard one, 4 out of 8 variants can maximize their effects in the rankings of the target token, and 3 variants can maximize their effects in the probabilities of the target token. The overlapped one is [plan-rank], and shows competitive performance on the generalization.

Among variants, [loc.-activ] and [plan-score] have low generalization scores but highest specificity score. On average, they make the ranking of the target token close to the argmax token, with a gap of 1.6 places, as indicated by their generalization MAE<sub>rank</sub> scores 1.661 and 1.608. However, as indicated by their specificity MAE<sub>rank</sub> scores 7.316 and 7.002, it makes the ranking of the target token rise by around 7 places. Since we only consider 10 top tokens, the two MENT variants tend to be over-fitting. By checking the actual predictions of the *probe set* after the editing, the target token is indeed promoted to 1st, 2nd, or 3rd in most cases.

Compared with the standard MENT, [loc.-activ] uses merely the neuron activations to locate buggy neurons, instead of considering both gradients and activations. Usually, gradients express features of the outputs while activations express features of the inputs. We deduce it tends to locate the neurons serving common knowledge, such as the code syntax, since they are likely to have larger activation values.

Similarly, [plan-score] directly uses the attribution score to estimate the editing-gains of buggy neurons. Since attribution scores are not precise in measuring the editing-gains, more neurons tend to be patched. That will deepen the effects of model editing on unrelated data and lengthen the editing process, so even though [plan-score] has low generalization scores, but has higher specificity scores and Avg. NC scores.

**Specificity.** For specificity, lower MAE scores indicate weak negative effects on unrelated data, as shown in Table 6. Besides two versions of KN, the MAE scores of 5 variants are lower on both ranking and probability than the standard one. Among them, [est.-switch] and [plan-rank] are better on the execution efficiency. Besides, as shown by MAE<sub>rank</sub> scores, MENT and most variants elevate the ranking of the target token to 5 places higher. It is acceptable since only the probabilities between the most top-ranked tokens have a gap, such as the top-3 tokens, while the other top tokens have close probabilities, such as from 4th to 10th.

Notably, high MAE scores in generalization promise low MAE scores in specificity. For example, [loc.-rand] has high generalization scores and low specificity scores, which means under-fitting, since it tends to skip resolving LLM errors, as revealed by the efficiency score. The two versions of KN are similar, and also, their Avg. NC scores are above 10 as well.

Based on our design, [est.-pathway] can be an alternative to the standard MENT. However, it has a longer editing process and requires more neurons to patch, as indicated by its Avg. NC score 4.231. That explains why its generalization scores are not that good. Considering [est.-pathway] edits only partial pathways of buggy neurons, instead of all, its side effects should be lighter than the standard MENT.

From an overall view, [est.-switch] and [plan-rank] are competitive choices, besides the standard MENT. They are eager to make effects but may be risky. For example, [est.-switch] uses a rough virtual probability distribution in the computation of neuron-parameter oracle, we doubt it might

introduce potential side effects. Similarly, [plan-rank] has an ignorance of the changes of token probabilities, so it might take less critical buggy neurons to edit. That will cause more neurons to edit and further introduce more side effects.

**RQ3 – Takeaway:** MENT strikes a favorable balance between generalization and specificity, rendering it more reliable than alternative approaches. Among the variants, [loc.-switch] and [plan-rank] are noteworthy but potentially risky, whereas [est.-pathway] is moderate yet safe.

## 5 RELATED WORK

Model editing is a relatively new topic, and there are not yet many methods proposed for it. These methods can be distinguished by the editing granularity, namely layer-level or neuron-level. Editing at the model layer level involves updating the parameters of involved neurons in specified layers in batches, which is similar to partial fine-tuning. On the other hand, editing at the neuron level involves locating neurons and modifying their activations or parameters.

However, prior work has several limitations. First, their tasks are limited to synonym replacement, for example, replacing a capital city from “Paris” to “Rome”. Second, their usage is limited as they require specifying an entity word as the trigger, such as “Eiffel Tower”, or preparing enough parallel data. Finally, their effects are limited, and they require massive or multiple times of editing, which leads to slow performance or obvious side effects. In contrast, our approach MENT has no such limitations.

There are two types of model editing based on whether additional components are introduced: intrinsic editing and extrinsic editing. Their difference is that intrinsic editing directly edits the parameters of the model by itself, while extrinsic editing introduces additional editable parameters along with the model.

Approaches like our MENT and the baseline KN [33] belong to intrinsic editing and are neuron-level model-editing. MENT is even pathway-level while maintaining its effectiveness, making it more lightweight than KN, which requires parallel data to locate neurons. Besides, MENT updates neurons by rewriting their parameters while KN amplifies their activations. ROME [34] and MEMIT [35] are model-editing techniques that edit decoder-only models on the layer level by specifying the layers to edit and then compute gradients to update parameters in batches. These techniques need to specify a trigger, so the data are limited to knowledge triples, limiting their use to a certain extent.

In contrast, extrinsic editing techniques are straightforward but lack potential. GRACE [47] utilizes codebooks between model layers to modify hidden representations, where codebooks are the combination of a classifier and a memory. MEND [48] and SERAC [32] apply to encoder-only models, decoder-only models, and encoder-decoder models. The former introduces a hyper-network for gradient decomposition, while the latter builds a parallel model to store edited behaviors and uses a classifier and a memory to decide which neural model to use. Overall, they are not editing the model but instead, tracking and responding to the model’s internal activity.

## 6 CONCLUSION

In this paper, we studied an emerging topic, which is model editing for coding tasks and LLM reasoning. In addition, we introduced a formal definition and new concepts to better clarify its process.

Targeted to assist generative LLMs in coding tasks, we proposed an effective, efficient, and reliable model editing approach MENT. In the experiments on code data and coding tasks, our approach performs well in terms of generalization and specificity. Based on our case study on direct and indirect chain-of-thoughts, model editing is extremely useful in guiding LLM’s reasoning.

In our subsequent research, we plan to explore applicable scenarios of model editing, especially tasks requiring high-quality reasoning. Meanwhile, we plan to seek further improvements, such as incorporating the editing strategy into the attribution process for better performance.

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