

Uncovering Failures of Model Editing in Large Language Models: An Improved Specificity Benchmark

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Abstract

Recent model editing techniques promise to mitigate the problem of memorizing false or outdated associations during large language model (LLM) training. However, we show that these techniques can introduce large unwanted side effects which are not detected by existing specificity benchmarks. We extend the existing COUNTERFACT benchmark to include a dynamic component and dub our benchmark COUNTERFACT+. Additionally, we extend the metrics used for measuring specificity by a principled \mathcal{KL} divergence-based metric. We use this improved benchmark to evaluate recent model editing techniques and find that they suffer from low specificity. Our findings highlight the need for improved specificity benchmarks that identify and prevent unwanted side effects.

1 Introduction

Large language models (LLMs) are powerful tools for generating human-like language, but they can, unfortunately, also memorize false or outdated associations, limiting their applicability. Model editing techniques promise to solve this problem by correcting non-factual associations. It is important that model edits are highly specific in the sense of not introducing any unwanted associations as a side effect. In this paper, we discuss why the current benchmark for specificity falls short and propose a more challenging, dynamic specificity benchmark to evaluate model editing techniques. Using this benchmark, we evaluate recent model editing techniques and find previously unreported side effects. Our findings highlight the importance of improved specificity benchmarks for the effective and safe use of LLMs.

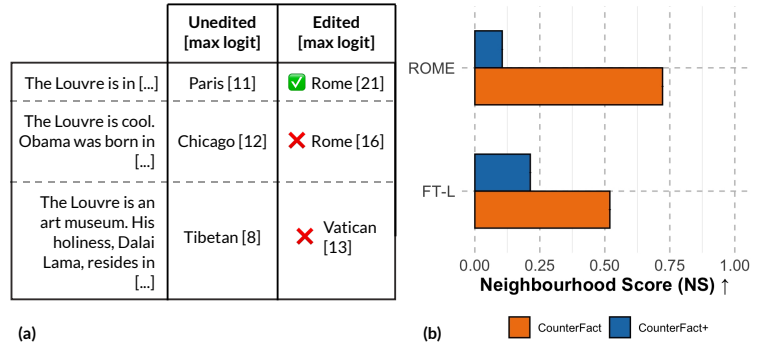


Figure 1: Unintended side effects of model edits and how to measure them. (a) GPT-2-medium is edited using ROME to counter-factually associate the Louvre’s location with Rome. However, this results in unintended associations ("loud facts") like the association of Obama with Rome, suggesting low specificity of the edit. The edit also significantly increases the maximum logit (shown in brackets), suggesting that the edit is not merely replacing "Paris" with "Rome" in the desired contexts. (b) Measuring specificity by the fraction of correctly completed test prompts (COUNTERFACT) suggests a high specificity for ROME. Prepending the edit prompt (like "The Louvre is in Rome.") to each test prompt (COUNTERFACT+) results in a significant drop in performance. A significant drop in measured specificity can also be observed if the model edit is implemented using constrained fine-tuning (FT-L).

Model editing updates the parameters of a trained model in order to change its predicted probability distributions without retraining the entire model. This can be used to edit the associations that the model has memorized and hence, improve the accuracy of the model. Fig. 1 shows the example of a counter-factual model edit using ROME (Meng et al., 2022a) where the location of the Louvre is edited to be Rome instead of Paris. We use a counter-factual example since it makes it more evident that the new association is an effect of the model edit instead of the model training. Note that

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the examples in Fig. 1 are not directly taken from the COUNTERFACT+ dataset introduced below, but serve to intuitively illustrate model editing failure modes we are interested in.

An important desideratum for model editing is specificity. Specificity captures how well the effect of the model edit is localized; in other words, specificity measures the absence of unintended side effects of model edits. Fig. 1 shows two examples of unintended side effects of ROME model editing, which we collectively call the problem of "loud facts". In the first example, mentioning "Louvre" (the subject of the model edit) leads the model to also complete unrelated test prompts ("Obama was born in") with "Rome" (the object of the model edit). In the second example, mentioning "Louvre" boosts the logits for words semantically related to "Rome", like "Vatican".

The existing specificity benchmark for model editing from the COUNTERFACT dataset suffers from two limitations which can be illustrated using these examples. First, COUNTERFACT does not prompt the model in a way that is likely to surface unwanted side effects. In the examples in Fig. 1, mentioning the subject of the model edit drastically changes the behavior of the edited model, but existing benchmarks do not detect this. Second, COUNTERFACT considers only the probabilities for the original and edited object token ("Paris" and "Rome"). In the last example in Fig. 1, the edited model displays strongly changed logits for words that are neither the original object ("Paris") nor the edit object ("Rome") but are semantically related to the edit object ("Vatican"). Again, this would be overlooked by the current specificity evaluation since it does not consider the entire probability distribution. These limitations make it difficult to detect unwanted side effects of model editing, meaning that specificity will be overestimated.

2 Related work

Model editing. Several studies have sought to localize and modify the computation of knowledge within transformers. Geva et al. (2021) proposed that the multilayer perceptron (MLP) layers in a transformer can act as key-value memories of entities and information associated with that entity. Dai et al. (2022) then demonstrated a method to edit knowledge within BERT by writing the embedding of the object into certain rows of the MLP matrix. They identified important neu-

rons for knowledge via gradient-based attributions. De Cao et al. (2021) presented a hyper-network to predict weight updates at test time, which can alter a fact. They tested both BERT and BART (Lewis et al., 2020) and focused on models fine-tuned for question answering. Mitchell et al. (2022) introduced a hyper-network method that learns to transform the decomposed terms of the gradient in order to efficiently predict a knowledge update and demonstrate the ability to scale up to large models such as T5 (Raffel et al., 2020), and GPT-J (Wang and Komatsuzaki, 2021). Finally, Meng et al. (2022a) introduced Rank-One-Model-Editing (ROME) which allows edits of transformer models via a rank-one modification of a single MLP layer. (Meng et al., 2022b) extended ROME to MEMIT (Mass-Editing Memory in a Transformer): MEMIT spreads the modification over multiple MLP layers; crucially, this enables thousands of simultaneous edits without performance degradation.

Model editing evaluation Benchmarks of model editing techniques for LLMs build on existing work on knowledge extraction from LLMs (see below). zsRE question answering was used for benchmarking model editing in (De Cao et al., 2021) and (Mitchell et al., 2022). Elazar et al. (2021) introduced ParaRel, a curated dataset of paraphrased prompts and facts. Meng et al. (2022a) use this as a basis for constructing COUNTERFACT, which enables fine-grained measurements of knowledge extraction and editing along multiple dimensions, including specificity.

Knowledge extraction from LLMs. The assessment of knowledge within language models (LMs) has typically been done by evaluating whether the model is able to predict pieces of knowledge; Petroni et al. (2019, 2020) defined a fill-in-the-blank prompt and asked the LM to complete it. Subsequent work has demonstrated that knowledge extraction can be improved by diversifying the prompts (Jiang et al., 2020; Zhong et al., 2021), or by fine-tuning a model on open-domain textual facts (Roberts et al., 2020). However, constructing prompts from supervised knowledge extraction data is still prone to learning new knowledge instead of recalling existing knowledge in an LM (Zhong et al., 2021).

3 Experimental Setup

3.1 Dataset

We investigate the specificity of recent model editing techniques using the COUNTERFACT benchmark introduced in (Meng et al., 2022a). COUNTERFACT is a collection of 21,919 non-factual statements of the form (subject, relation, object) (s, r, o^*) , which have low probabilities prior to the model edit. For each of these non-factual statements, we perform a model edit targeting this specific statement. To measure specificity, we then check whether any other associations in the model change in undesired ways. COUNTERFACT supports this check by providing a set of so-called neighborhood prompts for every non-factual statement used in the model edit. These neighborhood prompts are constructed as follows: For a model edit of the form $(s, r, o^c) \rightarrow (s, r, o^*)$ (where o^c is the correct object, and o^* is the false, counterfactual object), COUNTERFACT samples a set of nearby subjects s_n for which (s_n, r, o^c) holds true. Neighborhood prompts are then paraphrases of the collected (s_n, r) .

Suppose, for example, the edit request was $(\text{Darrieux}, \text{mother_tongue}, \text{French}) \rightarrow (\text{Darrieux}, \text{mother_tongue}, \text{English})$. COUNTERFACT takes the relation and object from the edit request $(\text{mother_tongue}, \text{French})$, samples true factual associations for this relation, object pair; e.g., $(\text{Montesquieu}, \text{mother_tongue}, \text{French})$ and then samples a random paraphrase, such as "The native language of Montesquieu is". These neighborhood prompts can be used to inspect whether the model edit has undesired side effects on closely related factual associations. See appendix C for a sample from the COUNTERFACT dataset, including the full set of neighborhood prompts.

Motivated by the example of loud facts shown in Fig. 1 and by the intuition that unwanted side effects are more likely when the model is primed with the linguistic context of the model edit, we now introduce a dynamic version of COUNTERFACT which we will refer to as COUNTERFACT+. To obtain COUNTERFACT+, we modify the neighborhood prompt by prepending the model edit. For example, if the original prompt is "The native language of Montesquieu is" the modified prompt would be "The mother tongue of Danielle Darrieux is English. The native language of Montesquieu is". See appendix D for a sample of the modified neighborhood prompts used for COUNTERFACT+.

To understand why we call COUNTERFACT+ a dynamic version of COUNTERFACT consider how either dataset would be applied to evaluate the success of a model edit: In both cases, we would need to identify the set \mathcal{N} of neighborhood prompts in the dataset that are semantically closest to the intended model edit. But in COUNTERFACT, we would use \mathcal{N} as is, whereas in COUNTERFACT+ we would change every prompt in \mathcal{N} as a function of the model edit, as described above.

3.2 Metrics

To evaluate the specificity of a model edit on COUNTERFACT, Meng et al. (2022a,b) use two metrics, called Neighborhood Score and Neighborhood Magnitude. Denoting the post-edit probabilities for the correct token o^c and incorrect edit token o^* by $P^*(o^c)$ and $P^*(o^*)$, respectively, these are defined as follows: The Neighborhood Score (NS) is defined as the fraction of neighborhood prompts for which $P^*(o^c) > P^*(o^*)$. The Neighborhood Magnitude (NM) is defined as $P^*(o^c) - P^*(o^*)$, the difference in probability assigned to the correct token versus the incorrect edit token. High NS and NM indicate that the edit has small unwanted side effects.

NS and NM, however, do not detect cases where the model edit leads to significant changes in the predicted probability distribution on tokens other than o^c and o^* , such as in the last example in Fig. 1. To capture this possibility, we introduce as an additional metric the *Kullback–Leibler* (KL) divergence on the next-token distribution between the edited and unedited model, referred to as Neighborhood KL Divergence (NKL). Abbreviating the next token probability distribution $P(w_t | w_{t-k}, \dots, w_{t-1})$ for the unedited and edited models by $P(w)$ and $P^*(w)$, respectively, and denoting the token vocabulary by \mathcal{W} , NKL is defined as KL divergence between $P(w)$ and $P^*(w)$:

$$\text{NKL} \stackrel{\text{def}}{=} \sum_{w \in \mathcal{W}} P(w) \log \left(\frac{P(w)}{P^*(w)} \right) \quad (1)$$

A large NKL implies that the next-token probability distribution for neighborhood prompts has been strongly affected by the model edit and is undesirable.

3.3 Models and Model Editing Algorithms

We run our experiments on GPT-2-medium (355M parameters), GPT-2-XL (1.5B) (Radford et al.,

2019), and GPT-J (6B) (Wang and Komatsuzaki, 2021). We evaluate the following model editing methods: ROME (Rank-One-Model-Editing) (Meng et al., 2022a), MEMIT (Mass-Editing Memory in a Transformer) (Meng et al., 2022b), and constrained Fine-Tuning (FT-L) with an L_∞ norm constraint (Zhu et al., 2020), as described in (Meng et al., 2022a). [add short inline descriptions of ROME, MEMIT, FT-L](#)

4 Results

Figure 2 shows the results for the ROME, MEMIT, and FT-L editing algorithms applied to the GPT-J-6B model for different specificity metrics and datasets considered in this work. When evaluated using the Neighborhood Score (NS), we observe significant drops in specificity across all of ROME, MEMIT, and FT-L when going from COUNTERFACT to COUNTERFACT+. Note that specificity measured on the unedited model (GPT-J-6B) also drops suggesting that there is some confounding from the test prompts in COUNTERFACT+, potentially due to recency bias (). The drop in specificity is much more pronounced for ROME, MEMIT, and FT-L, however. This shows that (a) all considered editing algorithms have undesired side effects and that (b) the improved benchmark COUNTERFACT+ is able to detect some of those unwanted side effects which are not detected by COUNTERFACT as originally defined. When evaluating specificity using the newly introduced Neighborhood KL Divergence (NKL), we observe a large spike in divergence for both ROME and MEMIT when going from COUNTERFACT to COUNTERFACT+. Interestingly, FT-L shows a much smaller increase in divergence from COUNTERFACT to COUNTERFACT+, albeit from an already high baseline. [improve statements on what we learn from considering KL divergence](#) Figure 3 in the appendix shows the results on COUNTERFACT and COUNTERFACT+ for the NM metric. [add prelim conclusions regarding scaling with model size plus pointers to the corresponding section in the appendix](#)

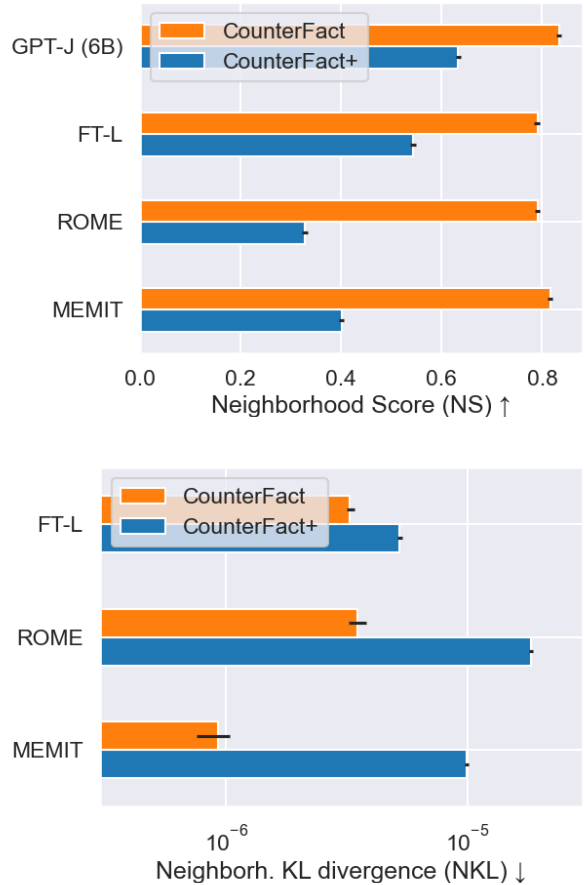


Figure 2: Comparison of model editing specificity benchmarks COUNTERFACT and COUNTERFACT+ on different model editing algorithms. (top) NS, the average fraction of correctly completed neighborhood test prompts after the model edit. We see that COUNTERFACT+ is a much more challenging specificity benchmark: Success rates NS on it range from 33% to 54% across different editing algorithms while they are close to 80% for COUNTERFACT. (bottom) NKL, the KL divergence of the next-token probability distribution of the edited model from that of the unedited model, averaged over all neighborhood test prompts. A lower value indicates higher specificity (the edited model behaves more like the unedited model). Error bars show 99% confidence intervals.

Results across all three models are shown in tables 1, 2, and 3. These tables list the mean scores on COUNTERFACT and COUNTERFACT+ for the Neighborhood Score (NS), Neighborhood Magnitude (NM), and Neighborhood KL divergence (NKL), respectively. The brackets give upper and lower bound of 99% confidence intervals obtained via bootstrap resampling ($N=1,000$). The bold values indicate the best score among the model editing algorithms for a given base model and dataset (excluding the unedited base model). Note how the method with the highest measured speci-

ficity switches from MEMIT/ROME to FT-L when going from COUNTERFACT to COUNTERFACT+.

| NS \uparrow | COUNTERFACT | COUNTERFACT+ |
|---------------|----------------------------|----------------------------|
| GPT-2 M | 0.75 (0.749, 0.757) | 0.46 (0.452, 0.463) |
| FT-L | 0.52 (0.515, 0.524) | 0.21 (0.209, 0.217) |
| ROME | 0.72 (0.718, 0.726) | 0.11 (0.102, 0.108) |
| GPT-2 XL | 0.78 (0.780, 0.788) | 0.52 (0.519, 0.530) |
| FT-L | 0.71 (0.702, 0.711) | 0.38 (0.375, 0.385) |
| ROME | 0.76 (0.755, 0.763) | 0.14 (0.135, 0.142) |
| MEMIT | 0.77 (0.770, 0.778) | 0.32 (0.314, 0.324) |
| GPT-J (6B) | 0.83 (0.830, 0.839) | 0.63 (0.628, 0.639) |
| FT-L | 0.79 (0.786, 0.795) | 0.54 (0.538, 0.550) |
| ROME | 0.79 (0.786, 0.796) | 0.33 (0.323, 0.333) |
| MEMIT | 0.82 (0.811, 0.820) | 0.40 (0.395, 0.407) |

Table 1: Neighborhood Score NS (μ & 99% CI) on COUNTERFACT and COUNTERFACT+.

| NM \uparrow | COUNTERFACT | COUNTERFACT+ |
|---------------|----------------------------|-------------------------------|
| GPT-2 M | 0.04 (0.035, 0.037) | 0.04 (0.038, 0.042) |
| FT-L | -0.02 (-0.019, -0.014) | -0.11 (-0.112, -0.106) |
| ROME | 0.03 (0.028, 0.030) | -0.32 (-0.324, -0.317) |
| GPT-2 XL | 0.05 (0.049, 0.052) | 0.08 (0.073, 0.078) |
| FT-L | 0.03 (0.033, 0.037) | 0.01 (0.012, 0.018) |
| ROME | 0.04 (0.042, 0.045) | -0.38 (-0.384, -0.375) |
| MEMIT | 0.05 (0.048, 0.050) | -0.06 (-0.059, -0.052) |
| GPT-J (6B) | 0.07 (0.073, 0.077) | 0.11 (0.111, 0.117) |
| FT-L | 0.07 (0.068, 0.072) | 0.09 (0.090, 0.096) |
| ROME | 0.05 (0.051, 0.056) | -0.12 (-0.127, -0.117) |
| MEMIT | 0.07 (0.066, 0.070) | -0.02 (-0.025, -0.017) |

Table 2: Neighborhood Magnitude NM (μ & 99% CI) on COUNTERFACT and COUNTERFACT+.

| NKL \downarrow | COUNTERFACT | COUNTERFACT+ |
|------------------|---------------------------|---------------------------|
| GPT-2 M | 0.0e+00 (0.0, 0.0) | 0.0e+00 (0.0, 0.0) |
| FT-L | 1.4e-05 (1.3, 1.4) | 1.4e-05 (1.3, 1.4) |
| ROME | 1.6e-06 (1.4, 1.7) | 2.5e-05 (2.5, 2.5) |
| GPT-2 XL | 0.0e+00 (0.0, 0.0) | 0.0e+00 (0.0, 0.0) |
| FT-L | 7.2e-06 (6.9, 7.4) | 9.5e-06 (9.3, 9.7) |
| ROME | 1.5e-06 (1.4, 1.6) | 3.3e-05 (3.2, 3.3) |
| MEMIT | 2.9e-07 (2.5, 3.4) | 9.0e-06 (8.8, 9.1) |
| GPT-J (6B) | 0.0e+00 (0.0, 0.0) | 0.0e+00 (0.0, 0.0) |
| FT-L | 3.2e-06 (3.1, 3.4) | 5.2e-06 (5.1, 5.3) |
| ROME | 3.5e-06 (3.2, 3.8) | 1.8e-05 (1.8, 1.9) |
| MEMIT | 9.2e-07 (8.0, 10) | 9.9e-06 (9.8, 10) |

Table 3: Neighborhood KL Divergence NKL (μ & 99% CI) on COUNTERFACT and COUNTERFACT+. Note that the order of magnitude is suppressed for the confidence interval for visual clarity; it is the same as for the mean.

5 Conclusion

We have shown that the ROME, MEMIT, and FT-L model editing techniques for autoregressive transformers suffer from problems with specificity, suggesting that model editing is far from being solved. We have also shown that for ROME and MEMIT, low specificity is only detected using COUNTERFACT+, a new specificity benchmark introduced in this paper. Our main contributions are:

- COUNTERFACT+, a dynamic specificity benchmark, which adapts to the model edit under test, and is more sensitive than the existing benchmark
- neighborhood KL divergence (NKL), a specificity metric based on the full probability distribution instead of the currently used metrics which focus only on the tokens directly implicated in the model edit.

Limitations

The main limitation of the approach we took for improving model editing benchmarks is that it is ultimately based on manual inspection of test cases to understand the failure modes of model editing methods. This approach is not scalable and has a significant cost in terms of time and effort. As far as the specific benchmark we propose is concerned, more research is needed to assess its effectiveness for more complex scenarios such as dialogue and

multi-turn conversations. We also have not investigated the application of our benchmark to scenarios in which multiple model edits are performed simultaneously. Furthermore, we do not evaluate other types of model edits, such as parameter pruning, and transfer learning. Finally, our benchmark does not consider the effect of data quality and data sparsity when measuring the impact of model edits on performance. Future work should focus on developing methods that measure and quantify the effects of model edits on long-term aspects of language models, such as their ability to capture discourse structure and fluency of generated text. This could include corpus-level analysis and dynamic approaches like red-teaming or dynamic benchmarking to uncover subtle adverse effects.

Ethics Statement

We do not perform human experiments or evaluation.

We are aware of the potential risks posed by autoregressive transformer models, such as the capabilities to generate and manipulate text for harmful purposes.

Our dataset and evaluation code is open-sourced at <https://github.com/jas-ho/specificityplus>, and we provide a homepage with interactive examples at <https://specificityplus.apartresearch.com/>.

Acknowledgements

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Our evaluation code builds directly on the MEMIT (Meng et al., 2022b) code open-sourced at <https://github.com/kmeng01/memit>.

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A Neighborhood magnitude

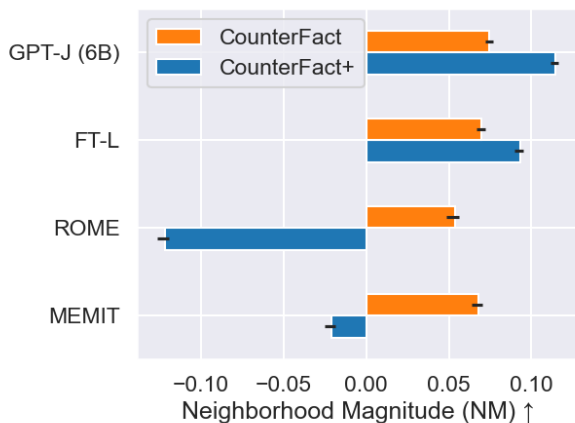
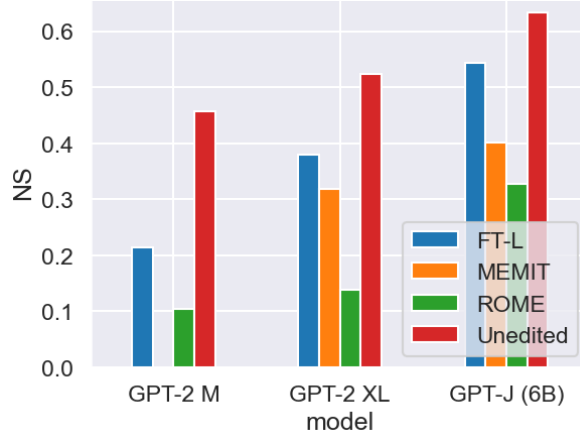


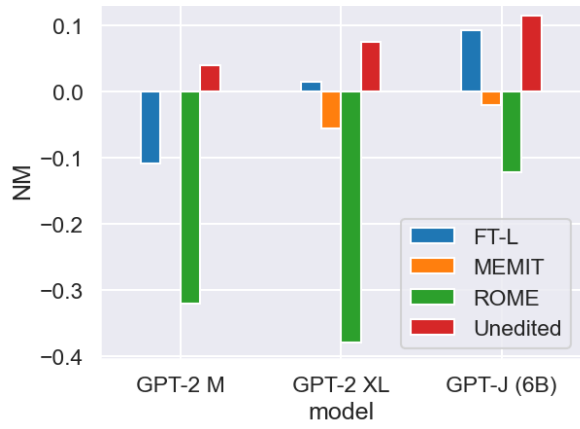
Figure 3: Comparison of model editing specificity benchmarks COUNTERFACT and COUNTERFACT+ evaluated using the Neighborhood Magnitude (NM) metric. NM measures the difference in probability of the correct token and the edit token. ROME retains almost the performance of the unedited model (GPT-J-6B) when evaluated on COUNTERFACT but shows a large drop in specificity when evaluated on COUNTERFACT+. FT-L also shows significantly lower performance on COUNTERFACT+ than on COUNTERFACT, albeit less dramatic than for ROME.

B Scaling with model size

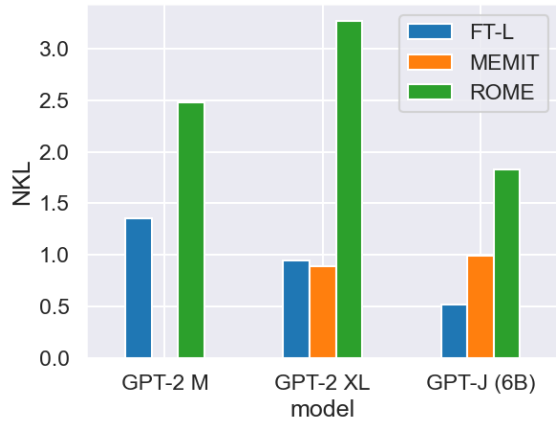
Figure 4 shows how performance on the COUNTERFACT+ dataset scales with the size of the underlying model. While the data does not allow conclusive statements there is preliminary evidence that specificity of the edited models improves for larger models. This is, however, partially confounded by improved specificity of the unedited model. It is therefore, at this point, not clear whether the specificity problems of ROME, MEMIT, and FT-L would disappear completely in the limit of extremely large models.[rethink this paragraph](#)



(a)



(b)



(c)

Figure 4: Evaluation of the model editing specificity benchmark COUNTERFACT+ on different model editing algorithms across model sizes. (a) NS, the average fraction of successfully completed neighborhood test prompts after the model edit. (b) NM, the difference in probability of the correct token and the edit token. (c) NKL, the KL divergence of the next-token probability distribution of the edited model from that of the unedited model, averaged over all neighborhood test prompts. A lower value indicates higher specificity (the edited model behaves more like the unedited model). Error bars show 99% confidence intervals.

C COUNTERFACT dataset sample

The listing below shows an example entry of the COUNTERFACT dataset. The "requested_rewrite" defines the model edit. The "neighborhood_prompts" are used for measuring specificity.

A sample of the COUNTERFACT dataset.

```
{
  "case_id": 0,
  "pararel_idx": 2796,
  "requested_rewrite": {
    "prompt": "The mother tongue of {} is",
    "relation_id": "P103",
    "target_new": {"str": "English", "id": "Q1860"},
    "target_true": {"str": "French", "id": "Q150"},
    "subject": "Danielle Darrieux"
  },
  "paraphrase_prompts": [
    "Shayna does this and Yossel goes still and dies. Danielle Darrieux, a native",
    "An album was recorded for Capitol Nashville but never released. Danielle Darrieux spoke the language"
  ],
  "neighborhood_prompts": [
    "The mother tongue of L\u00e9on Blum is",
    "The native language of Montesquieu is",
    "Fran\u00e7ois Bayrou, a native",
    "The native language of Raymond Barre is",
    "Michel Rocard is a native speaker of",
    "Jacques Chaban-Delmas is a native speaker of",
    "The native language of Fran\u00e7ois Bayrou is",
    "Maurice Genevoix, speaker of",
    "The mother tongue of Fran\u00e7ois Bayrou is",
    "Melchior de Vog\u00fc\u00e9, speaker of"
  ],
  "attribute_prompts": [
    "J.\u00a0R.\u00a0R. Tolkien is a native speaker of",
    "The mother tongue of Douglas Adams is",
    "...",
    "Meryl Streep, a native",
    "George Orwell spoke the language",
    "George Washington, a native", "Michael Jackson, a native"
  ],
  "generation_prompts": [
    "Danielle Darrieux's mother tongue is",
    "Where Danielle Darrieux is from, people speak the language of",
    "Danielle Darrieux's mother tongue is",
    "...",
    "Danielle Darrieux was born in"
  ]
}
```

D COUNTERFACT+ dataset sample

The listing below shows a sample of the COUNTERFACT+ dataset, which is derived from the sample shown above for COUNTERFACT. We only display the modified neighborhood_prompts which are obtained by prepending the model edit ("The mother tongue of Danielle Darrieux is English.") to the original neighborhood prompt.

A sample of the modified "neighborhood_prompts" in the CounterFact+ dataset.

```
[
  "The mother tongue of Danielle Darrieux is English. The mother tongue of
  ↳ L\u00e9on Blum is",
  "The mother tongue of Danielle Darrieux is English. The native language of
  ↳ Montesquieu is",
  "The mother tongue of Danielle Darrieux is English. Fran\u00e7ois Bayrou, a
  ↳ native",
  "The mother tongue of Danielle Darrieux is English. The native language of
  ↳ Raymond Barre is",
  "The mother tongue of Danielle Darrieux is English. Michel Rocard is a
  ↳ native speaker of",
  "The mother tongue of Danielle Darrieux is English. Jacques Chaban-Delmas is
  ↳ a native speaker of",
  "The mother tongue of Danielle Darrieux is English. The native language of
  ↳ Fran\u00e7ois Bayrou is",
  "The mother tongue of Danielle Darrieux is English. Maurice Genevoix,
  ↳ speaker of",
  "The mother tongue of Danielle Darrieux is English. The mother tongue of
  ↳ Fran\u00e7ois Bayrou is",
  "The mother tongue of Danielle Darrieux is English. Melchior de
  ↳ Vog\u00fc\u00e9, speaker of"
]
```