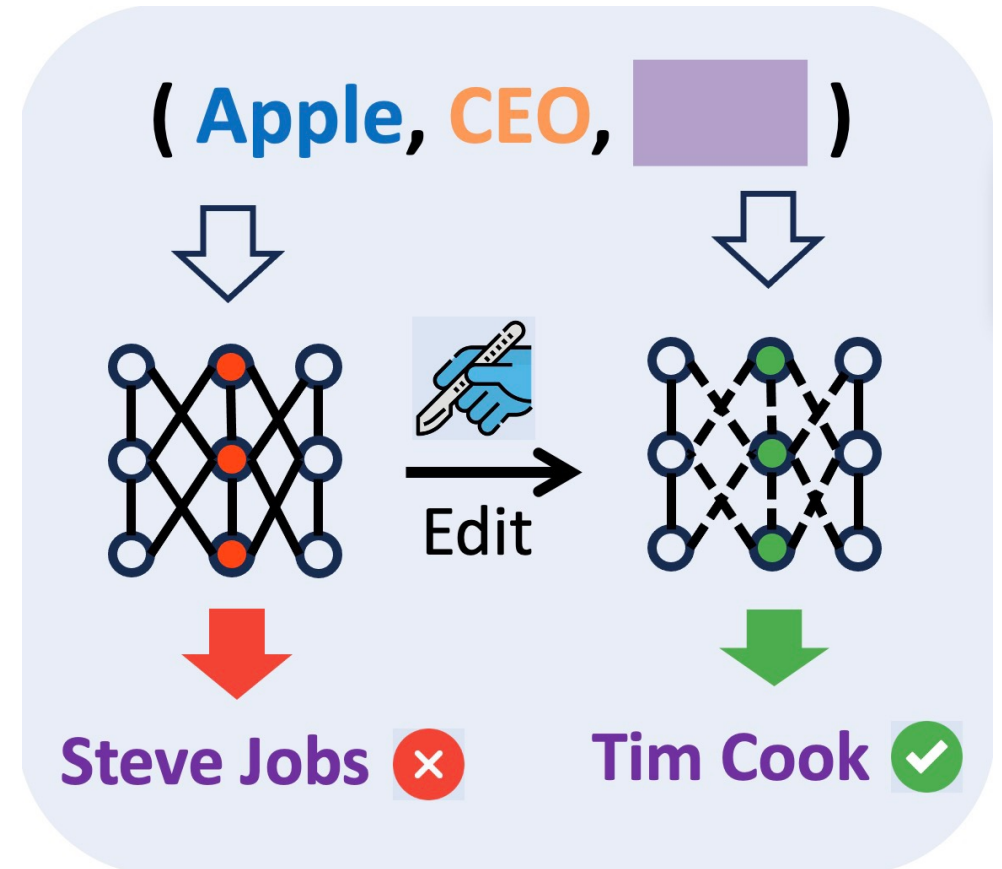


# Navigating the Dual Facets: A Comprehensive Evaluation of Sequential Memory Editing in Large Language Models

Zihao Lin, Mohammad Beigi, Lifu Huang  
April 5<sup>th</sup>, 2024, Virginia Tech

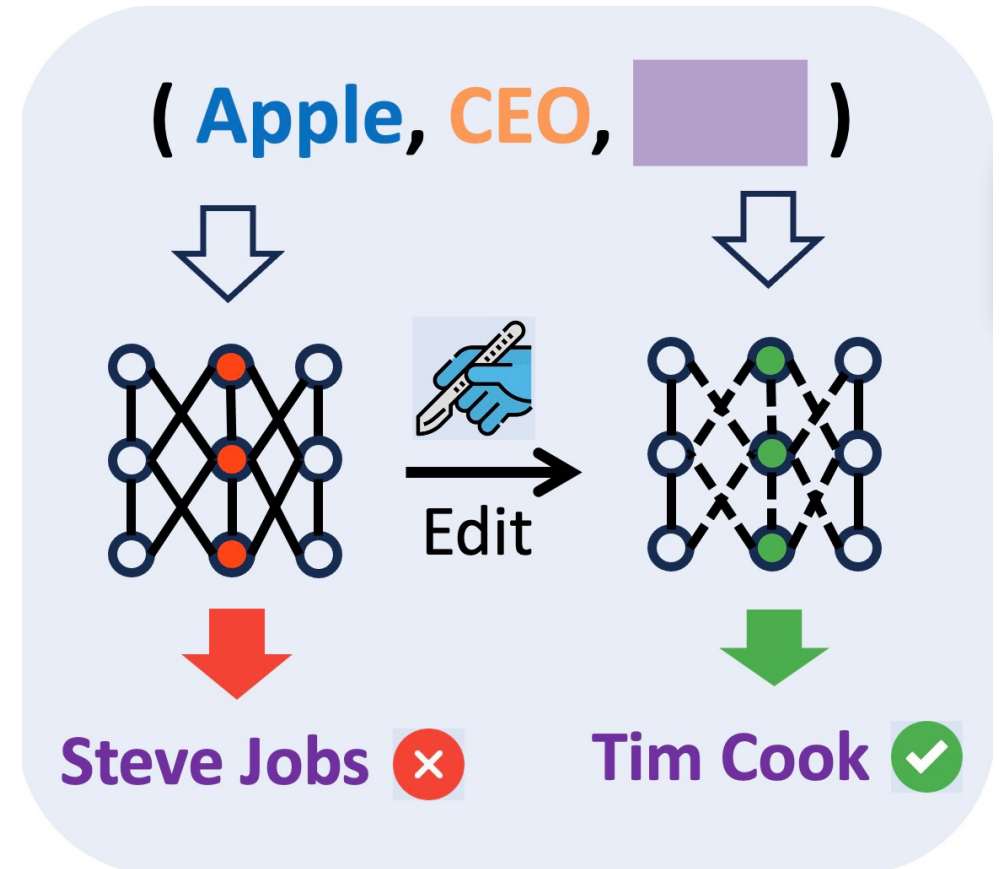
# What is Memory Editing?

- Memory Editing (ME) was introduced as an effective method to correct erroneous facts or inject new knowledge into Large Language Models (LLMs) without changing unrelated knowledge.



# What is Memory Editing?

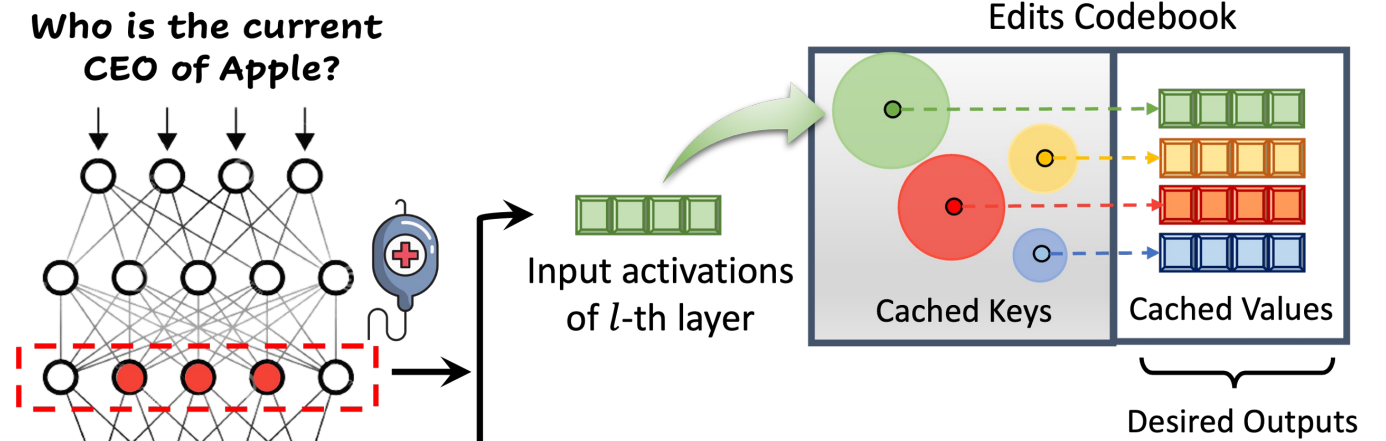
- Memory Editing (ME) was introduced as an effective method to correct erroneous facts or inject new knowledge into Large Language Models (LLMs) without changing unrelated knowledge.
- ME vs. Finetune:
  - ME does not change all the parameters of LLM.
  - ME is GPU & time efficient.



# Types of Memory Editing Methods

- Two categories of ME methods:
  - parameter-modifying ME methods
  - parameter-preserving ME methods

## (a) Parameter-preserving Methods

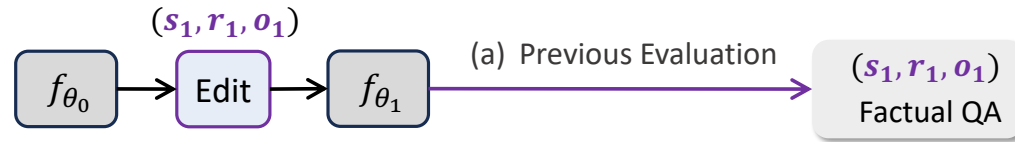


## (b) Parameter-modifying Methods



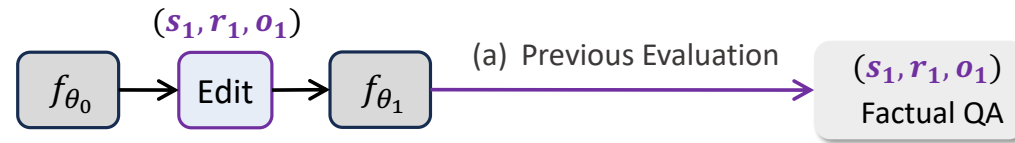
# Motivation

- Previous studies evaluating and analyzing ME methods have two critical limitations:
  - They only consider the performance of LLMs after every single editing.
  - They only concentrate on assessing ME's impact on factual knowledge (s, r, o).

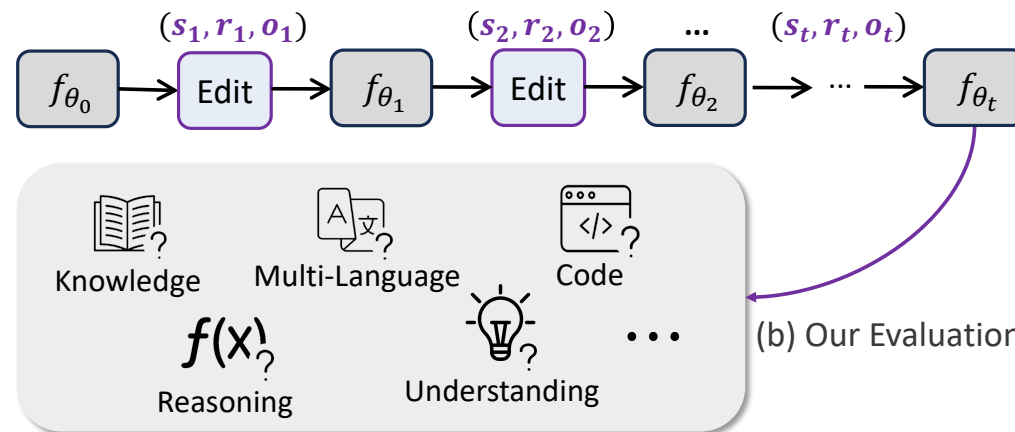


# Motivation

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  - They only consider the performance of LLMs after every single editing.
  - They only concentrate on assessing ME's impact on factual knowledge (s, r, o).



- To address these limitations, our study comprehensively evaluates the general capabilities of memory-edited LLMs in sequential editing scenarios.



# General Capabilities of LLMs

- Eight evaluation datasets across six main capabilities of LLMs:
  - Professional Knowledge: [MMLU](#) <sup>[1]</sup>
  - Common Sense Knowledge: [CommonsenseQA](#) <sup>[2]</sup>
  - Logical Reasoning: [MATH](#) <sup>[3]</sup>, [BBH](#) <sup>[4]</sup>, [SuperGLUE-AX-b](#) <sup>[5]</sup>
  - Reading Understanding: [C3](#) <sup>[6]</sup>
  - Multilingual Proficiency: [TyDiQA](#) <sup>[7]</sup>
  - Code Generation: [MBPP](#) <sup>[8]</sup>

# Memory Editing Methods

- Four memory editing methods across two categories:
  - Parameter-modifying ME methods:
    - MEND <sup>[9]</sup>
    - ROME <sup>[10]</sup>
    - MEMIT <sup>[11]</sup>
  - Parameter-preserving ME methods:
    - GRACE <sup>[12]</sup>



# Experiments Settings

- Large Language Models:
  - LLaMA-2-7b <sup>[13]</sup>
  - LLaMA-2-7b-Chat <sup>[13]</sup>
  - LLaMA-2-13b <sup>[13]</sup>
- Edit Dataset:
  - Randomly select 100 samples from the ZsRE <sup>[14]</sup> as the editing dataset.

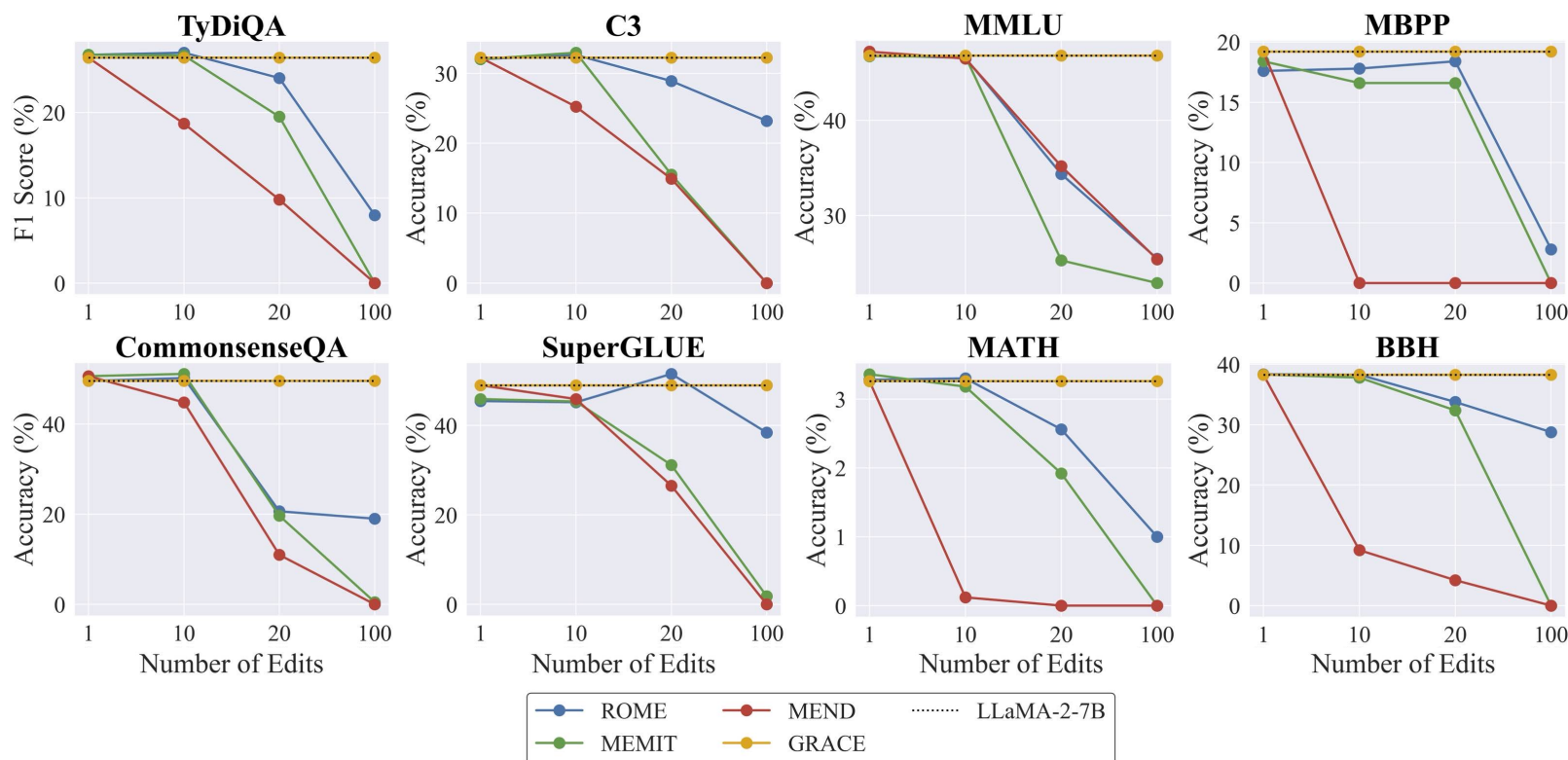
# Evaluating Results of Memory Editing

# Evaluation of Downstream Tasks

- Evaluate Llama-2-7b on eight downstream tasks.
- Sequentially edit 1, 10, 20, 100 times.

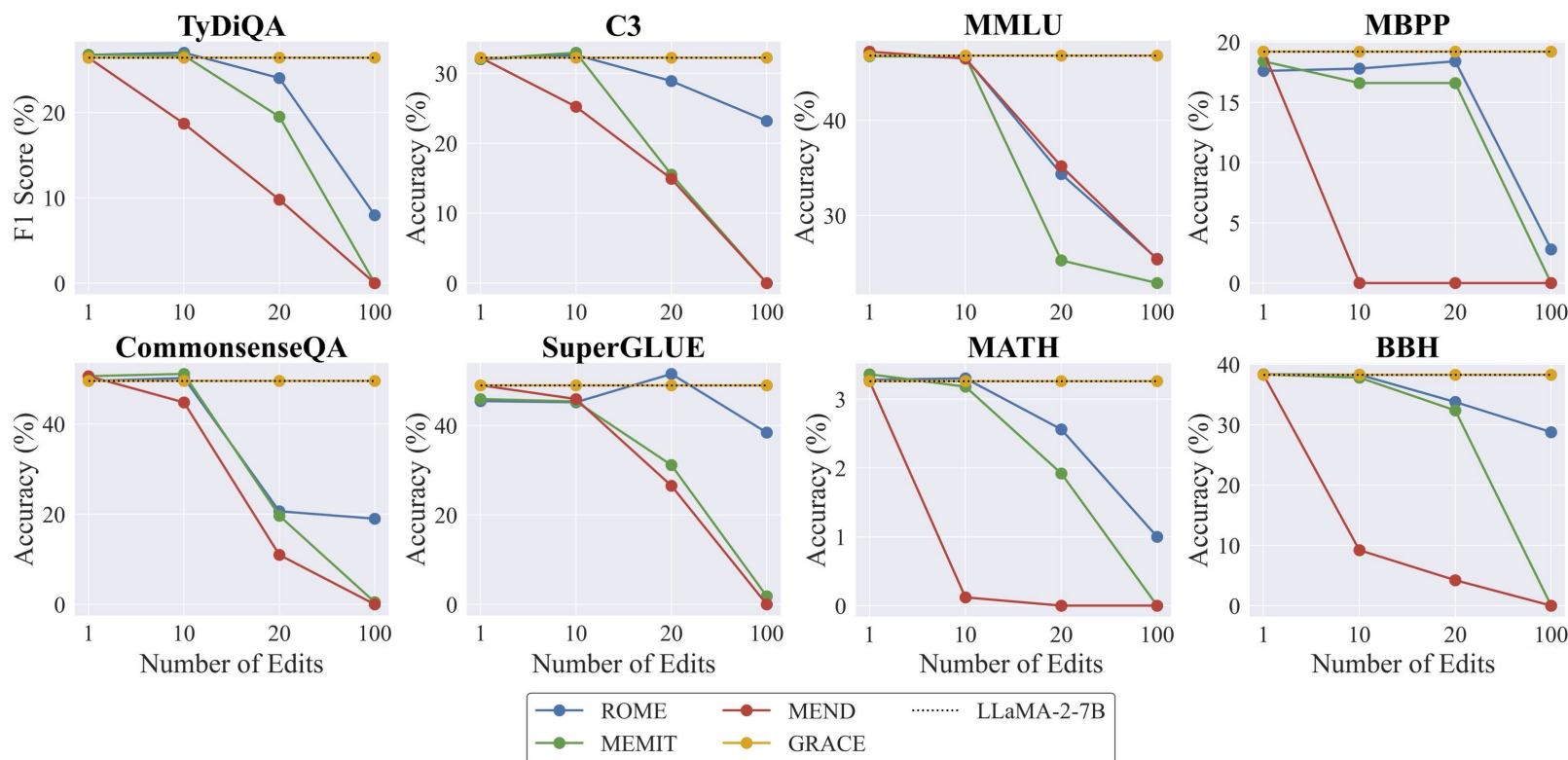
# Evaluation of Downstream Tasks

- Evaluate Llama-2-7b on eight downstream tasks.
- Sequentially edit 1, 10, 20, 100 times.
- Modifying-parameter ME methods systematically hurt the general capabilities of LLM after sequential editing.



# Evaluation of Downstream Tasks

- Evaluate Llama-2-7b on eight downstream tasks.
- Sequentially edit 1, 10, 20, 100 times.
- Parameter-preserving ME method, GRACE, maintains the broad capabilities of LLMs.

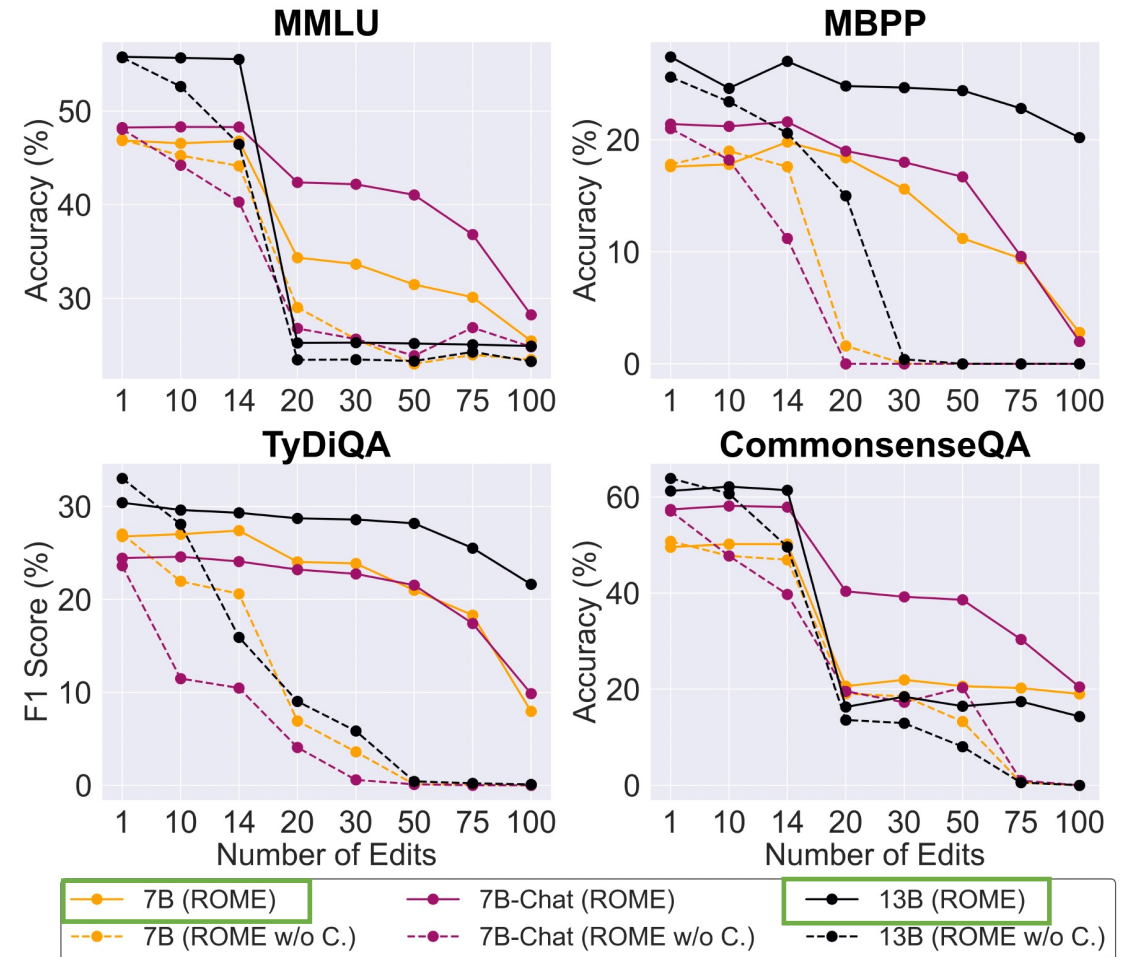


# Effect of Model Checkpoints and Size

- Evaluation Datasets:
  - MMLU: High school/College Examination
  - CommonsenseQA: Common Sense Question Answering
  - MBPP: [Code Generation](#)
  - TyDiQA: [Multi-language Understanding](#)

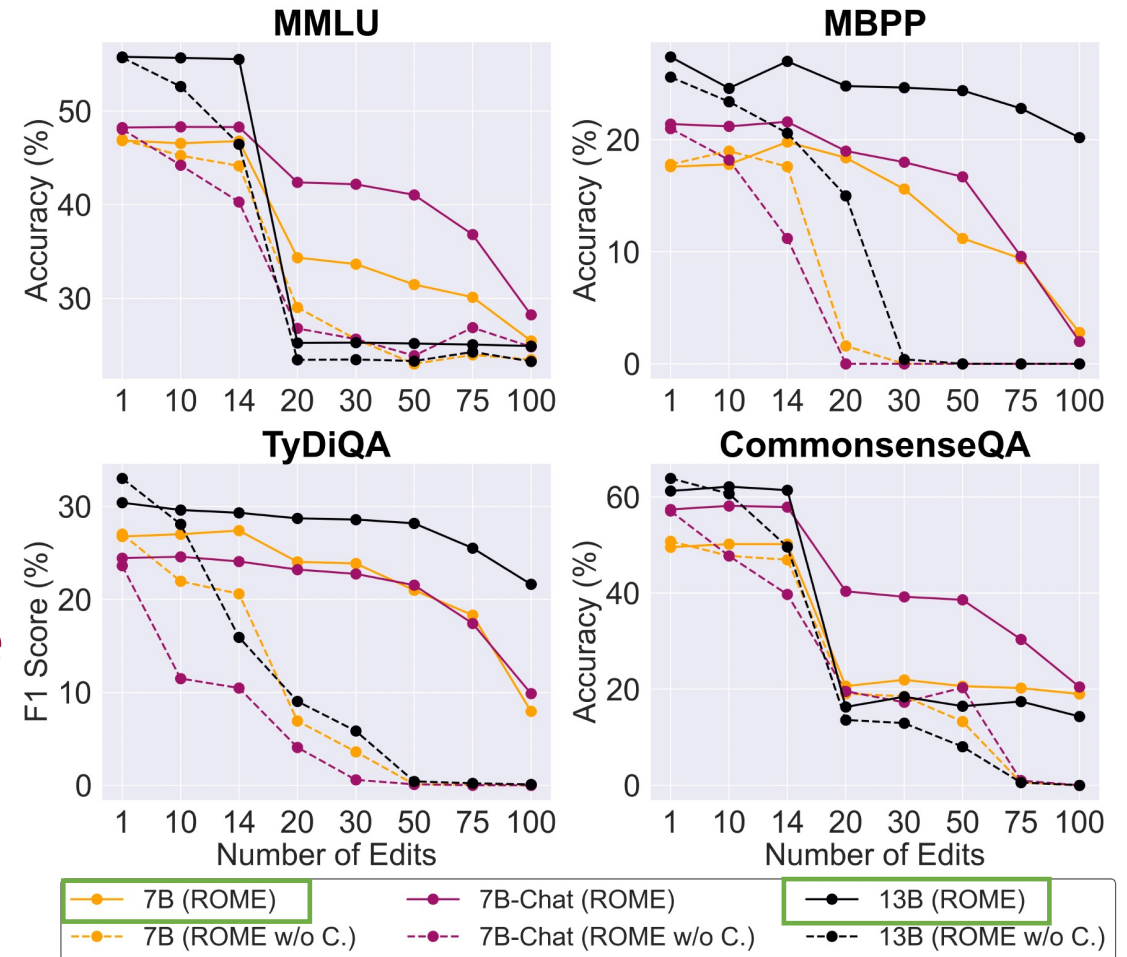
# Effect of Model Checkpoints and Size

- Evaluation Datasets:
  - MMLU: High school/College Examination
  - CommonsenseQA: Common Sense Question Answering
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  - TyDiQA: [Multi-language Understanding](#)
- Increasing models' parameters is beneficial to MBPP and TyDiQA.



# Effect of Model Checkpoints and Size

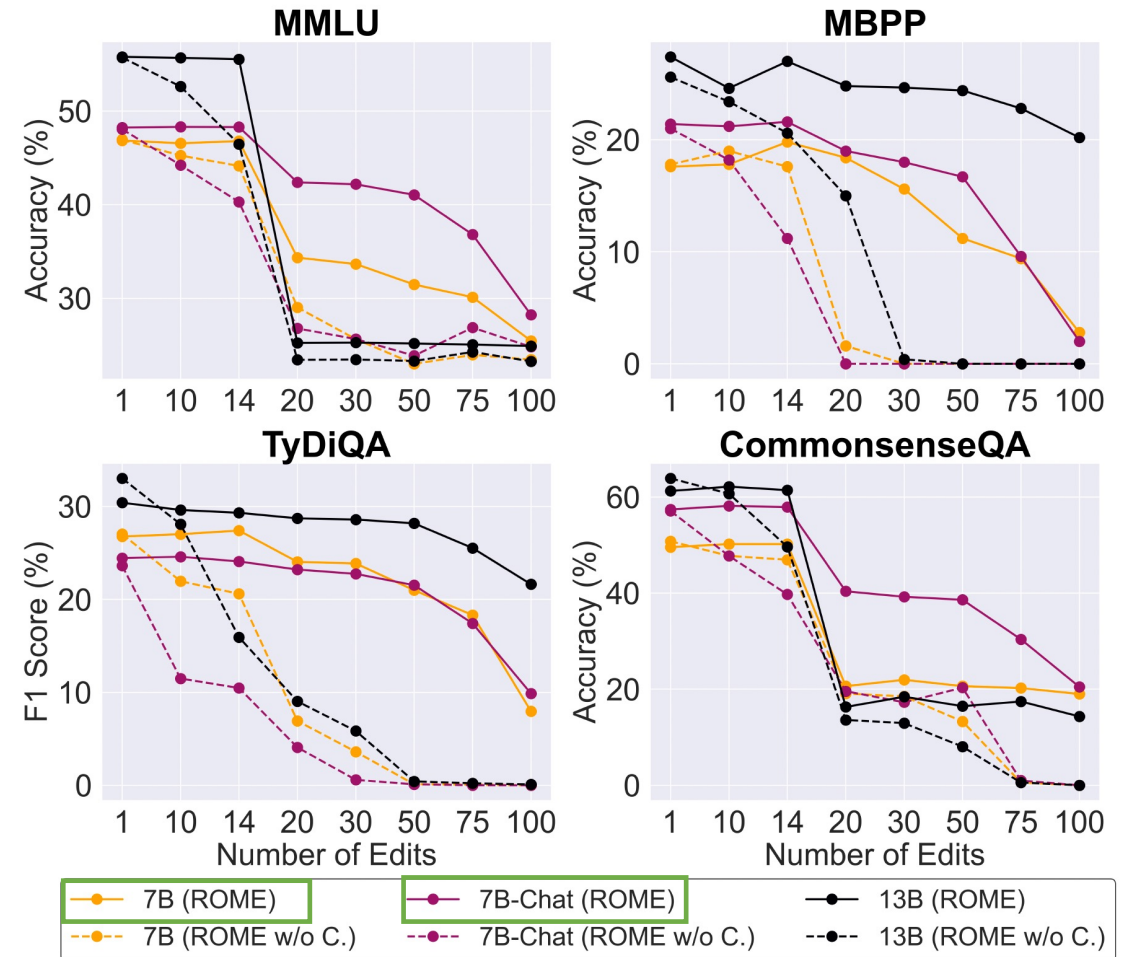
- Evaluation Datasets:
  - MMLU: High school/College Examination
  - CommonsenseQA: Common Sense Question Answering
  - MBPP: [Code Generation](#)
  - TyDiQA: [Multi-language Understanding](#)
- Hypothesis: more parameters mean that there are enough parameters to store different knowledge in different parameters, which reduces the negative influence.





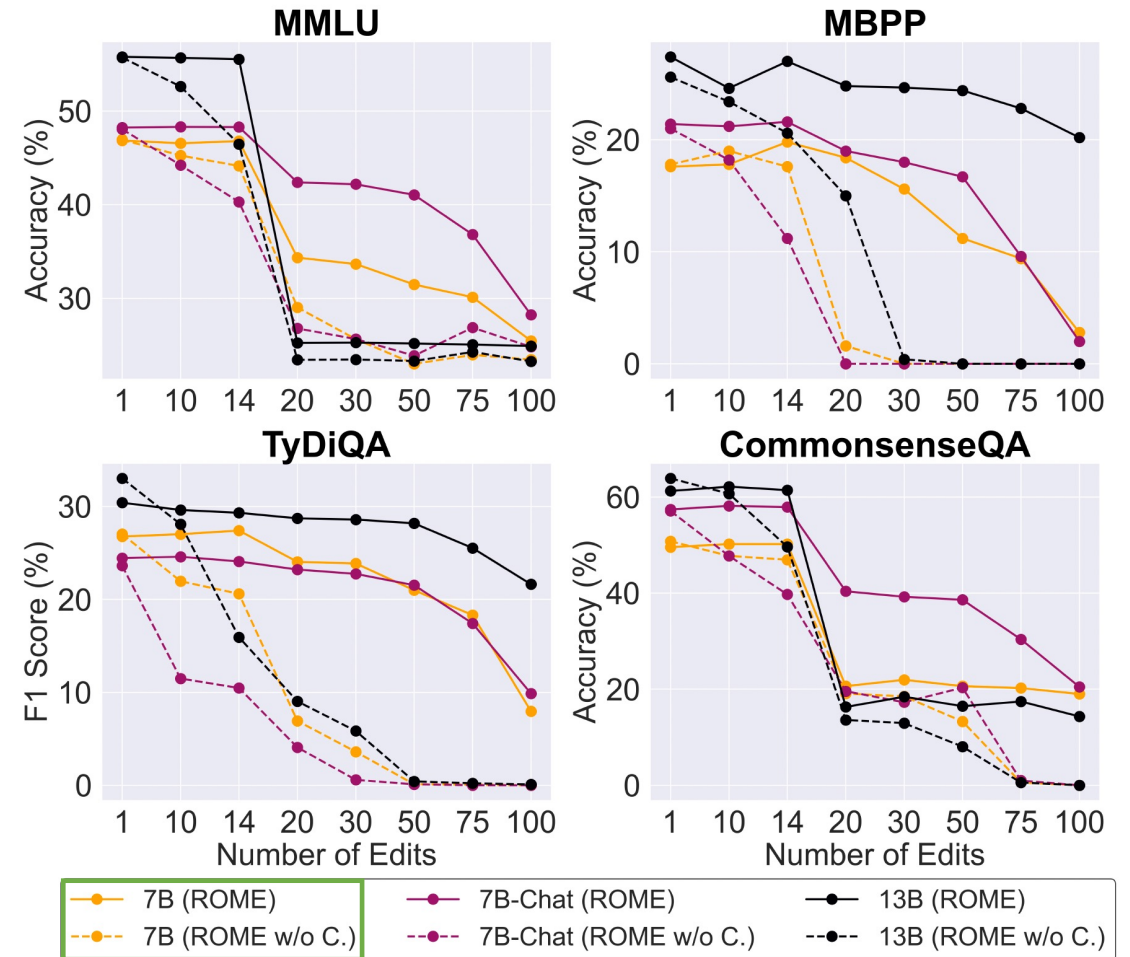
# Instruction Tuning and Its Implications

- After instruction tuning, the model has more robustness on MMLU and CommonsenseQA, whose inputs are also similar to dialogue in English.



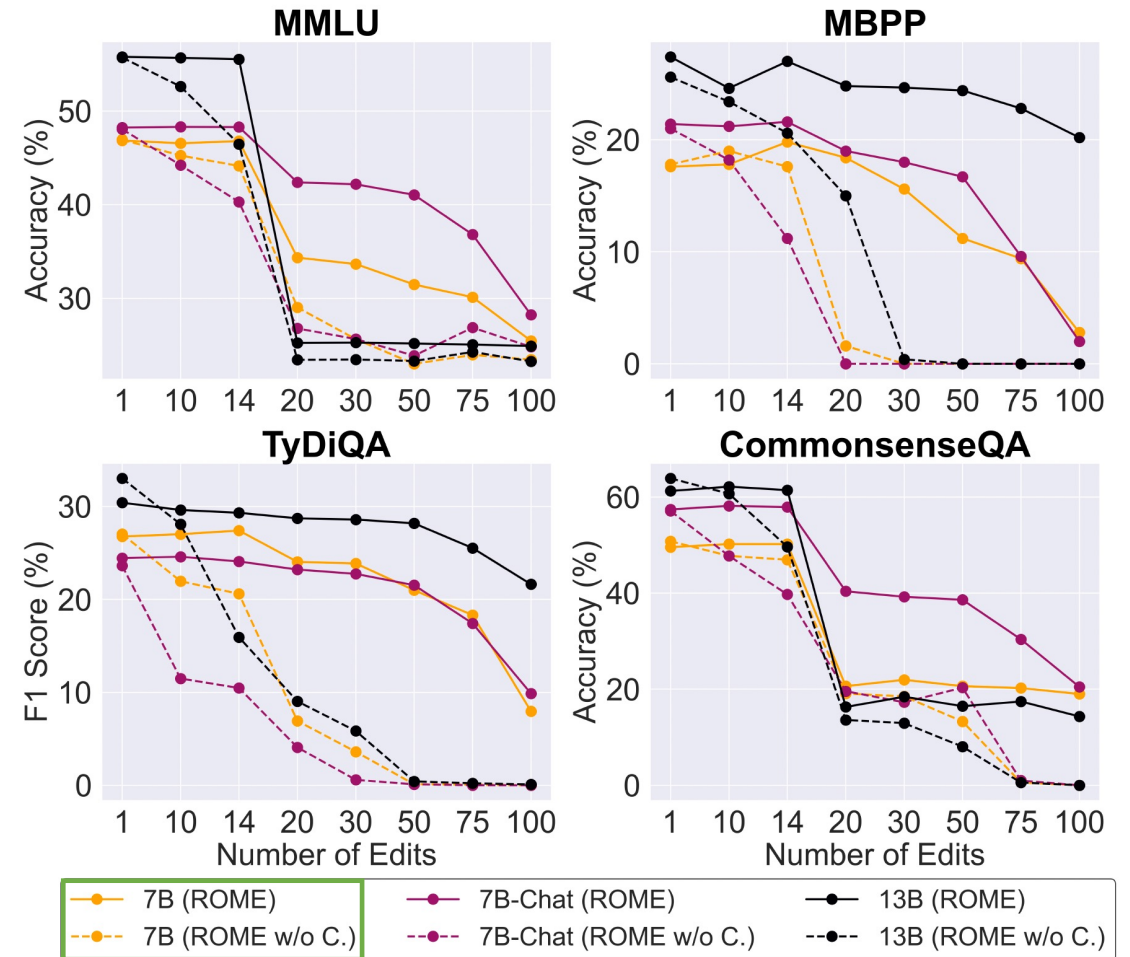
# Constraint Methods in ROME

- ROME utilizes 100,000 Wiki Knowledge, which is unrelated to edited knowledge, and applies a constraint method to avoid the edited LLM forgetting some unrelated knowledge.



# Constraint Methods in ROME

- ROME utilizes 100,000 Wiki Knowledge, which is unrelated to edited knowledge, and applies a constraint method to avoid the edited LLM forgetting some unrelated knowledge.
- Adding constraints is beneficial to maintain general capabilities during sequential editing but cannot fully avoid such damage.

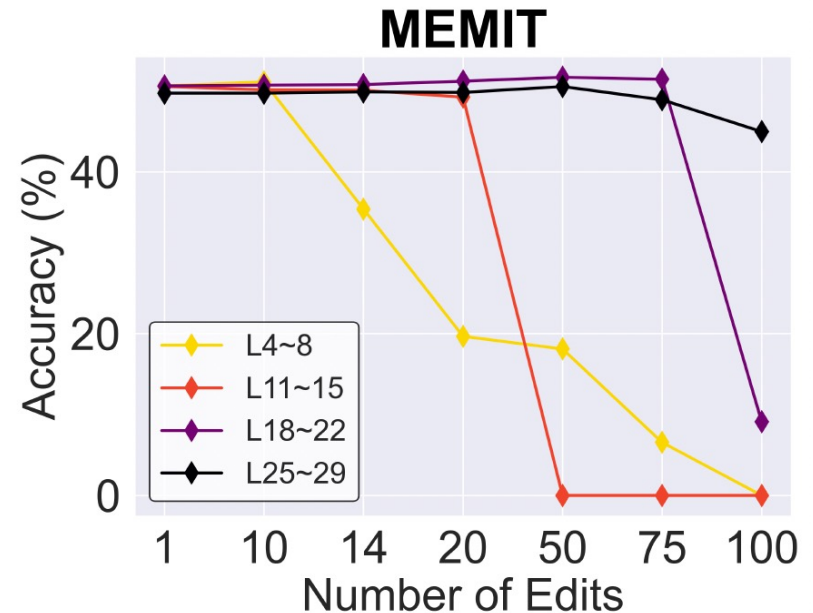
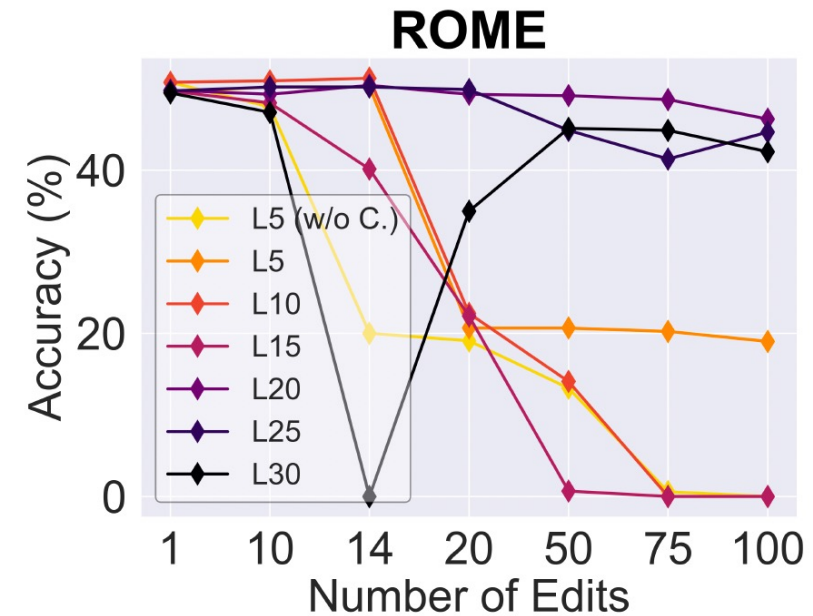


# Layers to Edit

- Methods:
  - ROME: Edit one FFN layer
  - MEMIT: Edit five FFN layers
  - Evaluate the CommonsenseQA dataset.

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- Methods:
  - ROME: Edit one FFN layer
  - MEMIT: Edit five FFN layers
  - Evaluate the CommonsenseQA dataset.
- The choice of layers for editing in LLMs significantly impacts their general capabilities, with deeper layers showing more resilience to the editing process than shallower ones.



Thanks!

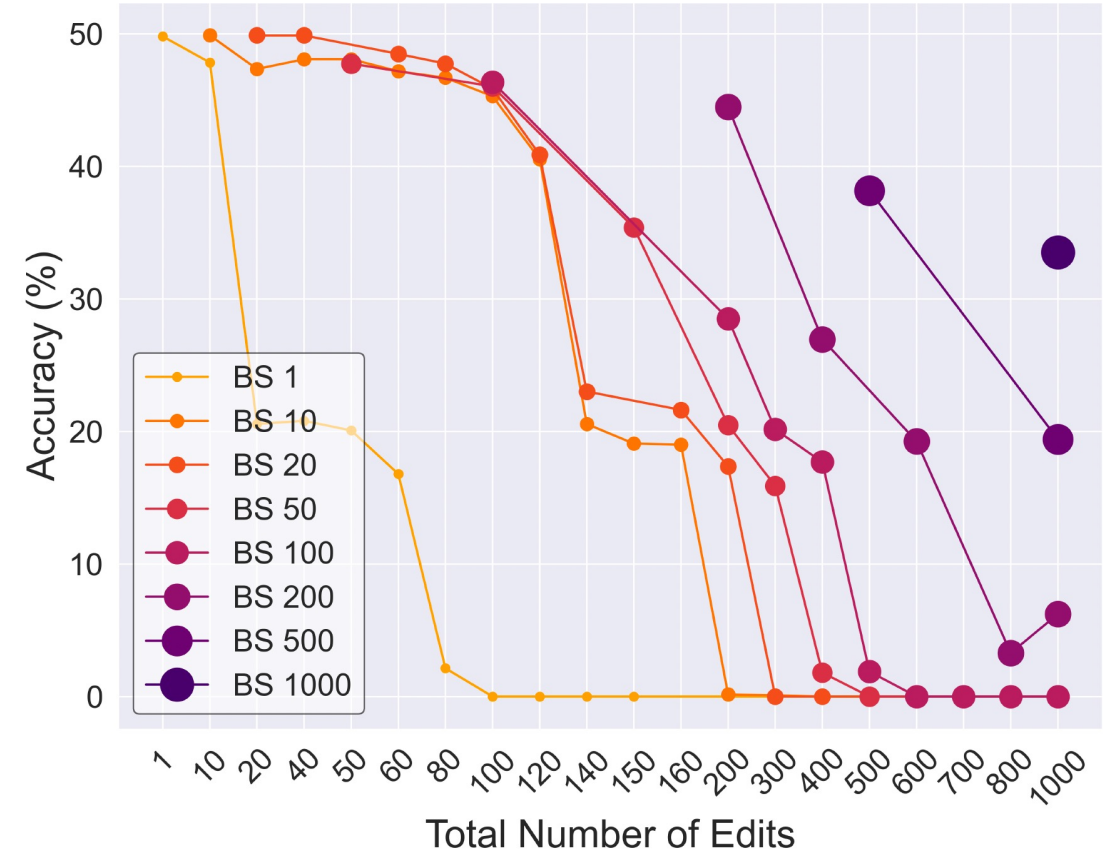
Q & A

# Batch Size of Editing

- Methods:
  - MEMIT: Edit five FFN layers
  - Evaluate on CommonsenseQA dataset.

# Batch Size of Editing

- Methods:
  - MEMIT: Edit five FFN layers
  - Evaluate the CommonsenseQA dataset.
- With the same number of edit triples, increasing the batch size means reducing the number of editing times, which turns out to be beneficial in mitigating the damage of ME to LLMs.



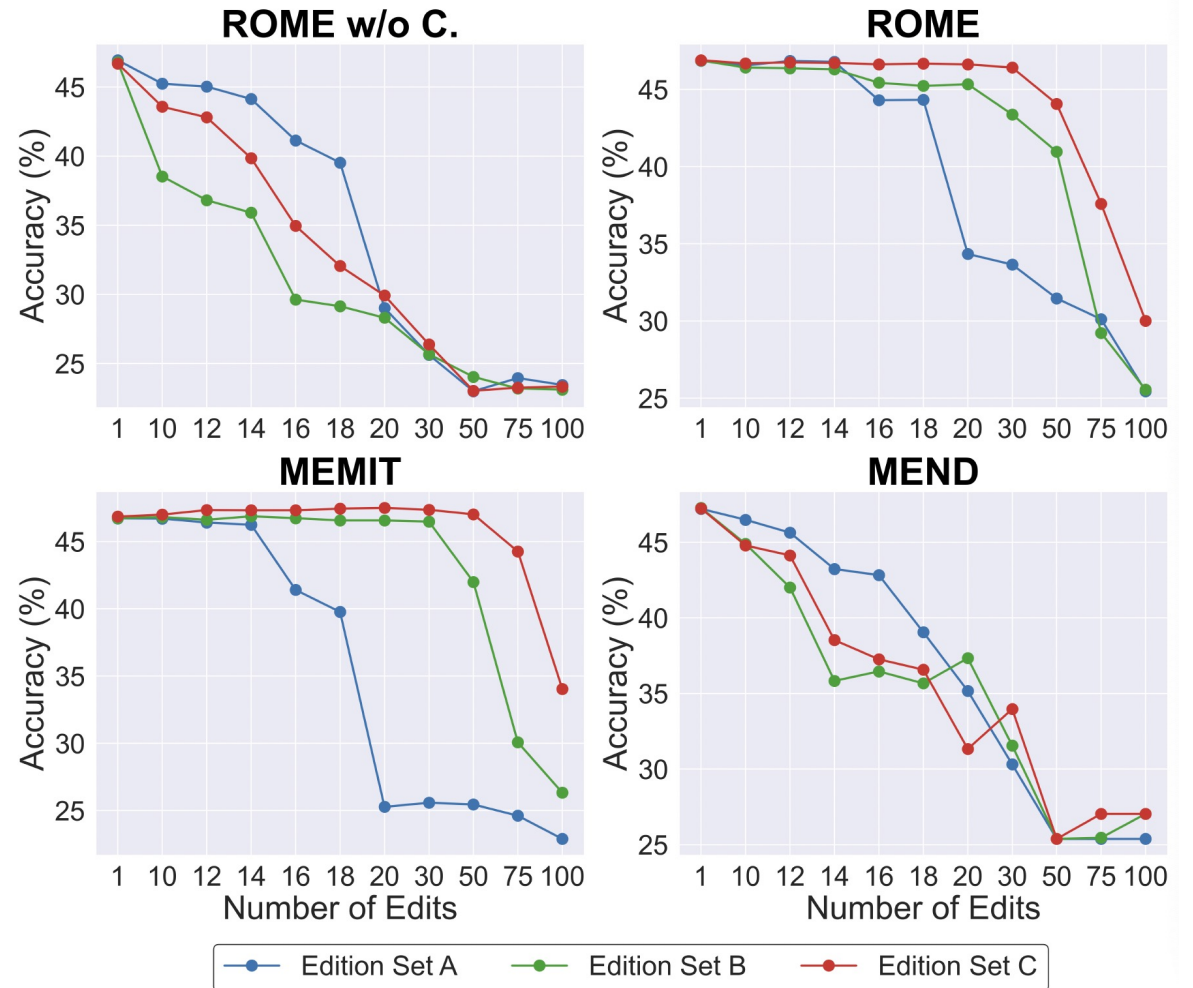


# Different Editing Data

- Methods:
  - Randomly select 100 samples from the ZsRE dataset three times without overlapping.
  - Evaluate on CommonsenseQA.

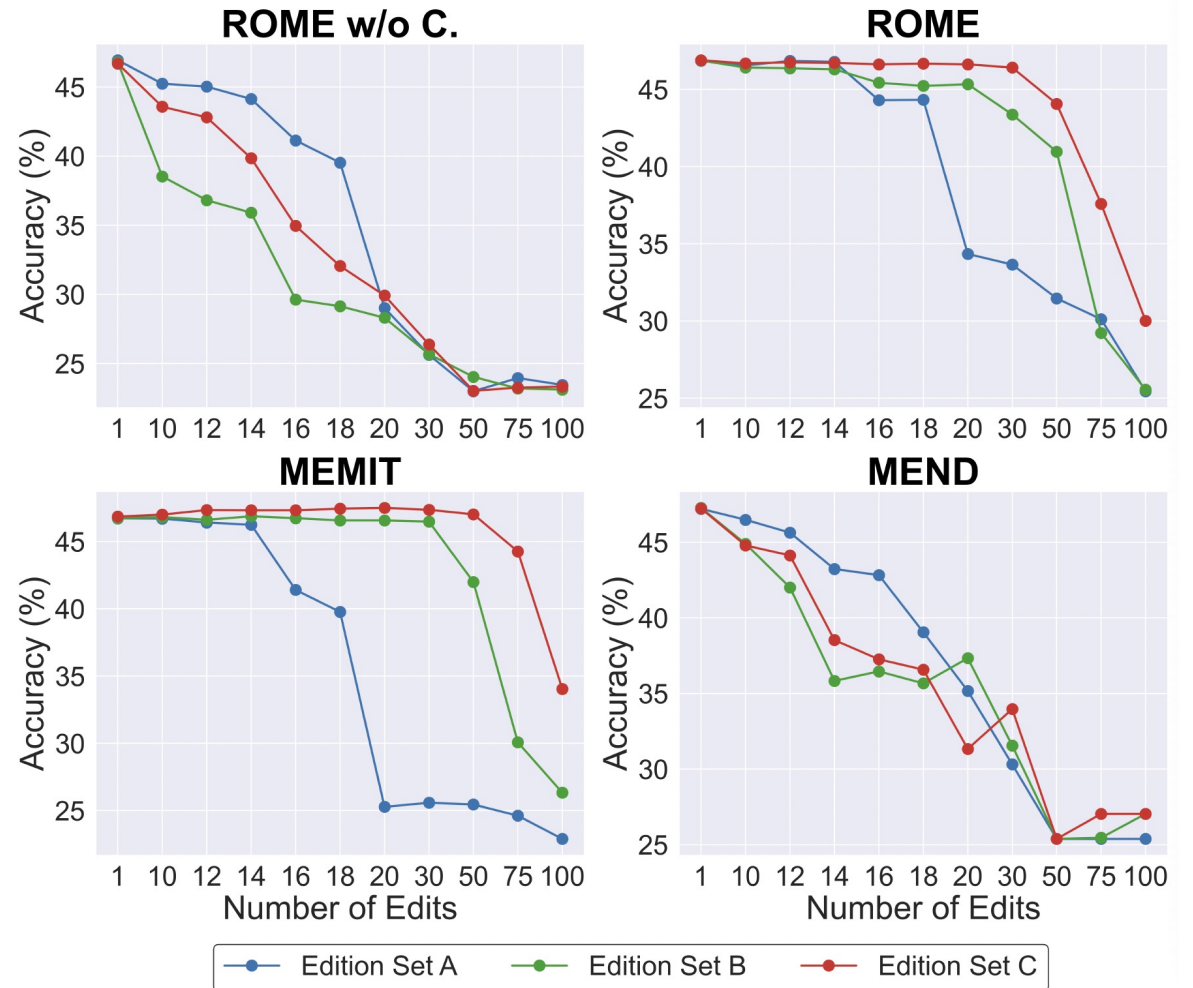
# Different Editing Data

- Methods:
  - Randomly select 100 samples from the ZsRE dataset three times without overlapping.
  - Evaluate on CommonsenseQA.
- Under different editing sets, parameter-modifying ME methods systematically destroy the power of the language model after 100 edits.



# Different Editing Data

- Methods:
  - Randomly select 100 samples from the ZsRE dataset three times without overlapping.
  - Evaluate on CommonsenseQA.
- The difference in damage trends comes from the effect of editing the data on the model.



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