Avoiding Copyright Infringement via Large Language Model Unlearning

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Abstract

Pre-trained Large Language Models (LLMs) have demonstrated remarkable capabilities but also pose risks by learning and generating copyrighted material, leading to significant legal and ethical concerns. In real-world scenarios, model owners need to continuously address copyright infringement as new requests for content removal emerge at different time points. This leads to the need for sequential unlearning, where copyrighted content is removed sequentially as new requests arise. Despite its practical relevance, sequential unlearning in the context of copyright infringement has not been rigorously explored in existing literature. To address this gap, we propose **S**table **S**equential **U**nlearning (**SSU**), a novel framework designed to unlearn copyrighted content from LLMs over multiple time steps. Our approach works by identifying and removing specific weight updates in the model's parameters that correspond to copyrighted content. We improve unlearning efficacy by introducing random labeling loss and ensuring the model retains its general-purpose knowledge by adjusting targeted parameters. Experimental results show that SSU achieves an effective trade-off between unlearning efficacy and general-purpose language abilities, outperforming existing baselines. [1]

1 Introduction

In December 2023, the New York Times filed a lawsuit against OpenAI, accusing it of training its Large Language Models (LLMs) on copyrighted material without permission[3]. This legal challenge highlights the growing concern over LLMs incorporating copyrighted content from vast pre-training datasets, which are often composed of publicly available text (Brittain, 2023; Rahman and Santacana, 2023). Despite the significant progress LLMs

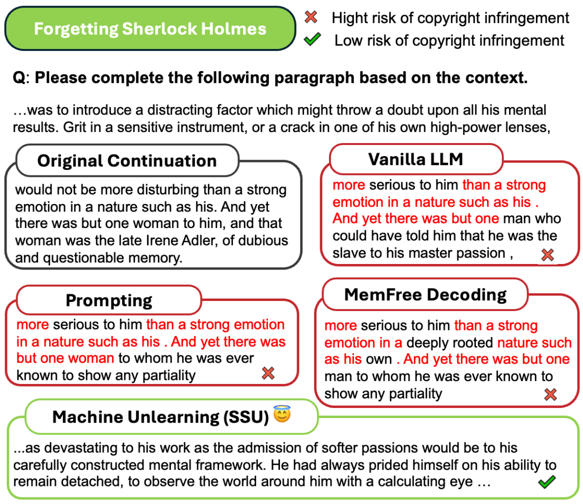

Figure 1: Continuations of a passage from Sherlock Holmes under different copyright takedown methods. The original continuation serves as the ground truth. The vanilla model, prompting, and MemFree decoding exhibit high risk of copyright infringement. In contrast, SSU produces a continuation that is transformative to avoid copyright infringement. [2]

have made through learning from diverse text data (Brown et al., 2020; Chowdhery et al., 2023; Touvron et al., 2023), screening out copyrighted material remains an immense challenge (Duarte et al., 2024). These issues raise broader questions about fair use of generative models.

There are two times when copyright interacts with LLMs. The first is when LLMs learn from copyrighted materials, which is arguably fair use (but this has not been tested in court). The second is when LLMs generate outputs. If a generated output is substantially similar to copyrighted work it has trained on, then this is more likely to be a copyright infringement. If a court found an AI model developer to be in violation of copyright, then the court may require that the developer to remove that copyrighted work from the model. The cost of retraining from scratch leaving out one copyrighted work is exorbitantly high. Therefore, as an alternate remedy, a court may ask for a copyright

[1]Code is available at guangyaodou/SSU.

[2]This example is for illustration purposes only, as Conan Doyle's Sherlock Holmes entered the public domain in 2023.

[3]NYT Complaint, Dec 2023

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takedown that does not require a full retraining of the model. This motivates research into unlearning and other copyright takedown methods.

Previous works have investigated post-hoc copyright takedown methods – mitigating risks of generating copyrighted contents – using system prompt and decoding time intervention such as the MemFree Decoding (Ippolito et al., 2022). Additionally, an alternative solution is *machine unlearning* (Cao and Yang, 2015), which removes unwanted knowledge after pre-training, reconfiguring the model as if it had never learned that data (Figure 1). Recent works proposed practical machine unlearning algorithms for LLMs (Zhang et al., 2024; Chen and Yang, 2023; Jang et al., 2023; Zhao et al., 2024). However, few have addressed the challenge of *sequentially* unlearning copyrighted content, where multiple unlearning requests must be processed over time without retraining from scratch. A key difficulty lies in controlling the changes in model weights during this process—existing methods often struggle to prevent unintended drift, leading to drastic degradation of general-purpose language abilities, leaving it unclear if they are suitable as copyright takedown methods. An effective unlearning algorithm should be *stable*, meaning it should ensure *unlearning efficacy* while preserving non-targeted knowledge, knowledge that are not subject to unlearning, and general-purpose abilities.

The core of many previous LLM unlearning methods have focused on Gradient Ascent (GA) and further combined it with an in-distribution retained dataset to preserve general-purpose language abilities, known as Gradient Difference (Maini et al., 2024; Zhao et al., 2024; Liu et al., 2024e; Yao et al., 2024). However, Gradient Difference requires collection of a substantial amount of in-distribution retained data to maintain general-purpose abilities. Moreover, GA-based methods risk catastrophic collapse, where the model's general-purpose language abilities degrade significantly (Liu et al., 2024e). Zhang et al. (2024) proposed Negative Preference Optimization (NPO), framing unlearning as preference optimization. However, NPO relies on a reference model, and if the reference model contains copyrighted information, unlearning efficacy is compromised.

To address these challenges in sequentially unlearning copyrighted books, we propose **S**table **S**equential **U**nlearning (SSU), that achieves a better trade-off between effective unlearning and maintaining general-purpose language abilities in sequential settings. Specifically, SSU first fine-tunes the model on the copyrighted books, followed by fine-tuning with random labels. During gradient updates, SSU applies targeted weight adjustments through weight saliency. Afterwards, it extracts task vectors (Ilharco et al., 2022) corresponding to the copyrighted books and subsequently negates these task vectors to achieve unlearning. Unlike Gradient Difference methods, SSU does not require additional retained data collection to maintain its performance on other tasks, thereby avoiding the complexity and overhead associated.

Our experiments on the Llama-3.1-8B-Instruct (Dubey et al., 2024) and Mistral-7B-Instruct-v0.3 (Jiang et al., 2023) show that SSU achieves a superior trade-off between unlearning efficacy and general-purpose language abilities, avoiding the catastrophic collapse. Moreover, SSU consistently outperforms NPO, which employs preference optimization frameworks. Additionally, fine-tuning with random loss and targeted model updates play distinct roles in facilitating the unlearning process within SSU. In contrast, copyright takedown methods that do not involve model weight updates, such as system prompts and MemFree Decode, fail to mitigate the risks of copyright infringement.

Our main contributions are:

- We present the first investigation into the sequential unlearning of copyrighted literary works to address copyright infringement, formalizing the task and defining evaluation metrics for effectiveness.
- We propose SSU, a stable unlearning algorithm for sequential settings, which achieves a superior trade-off between mitigating copyright infringement and preserving reasoning capabilities compared to existing methods.
- We systematically evaluate existing methods within the sequential unlearning setting and demonstrate that they either provide limited mitigation of copyright infringement or suffer from catastrophic collapse.

2 Related Work

LLM Memorization and Copyright LLMs are known to memorize and reproduce training data from the pre-training stage (Carlini et al., 2021, 2022; Zhang et al., 2023; Nasr et al., 2023; Liu et al., 2024b). This behavior has prompted recent studies exploring the connection between verbatim memorization and copyright infringement (Chu et al., 2024; Huang et al., 2024; Meeus et al., 2024; Karamolegkou et al., 2023), as well as the fair use of foundation models (Henderson et al., 2023). Various methods have been proposed to mitigate these risks. For instance, Ippolito et al. (2022) introduced the MemFree decoding to reduce the likelihood of copyright infringement but failed to capture non-consecutive verbatim content. Additionally, Min et al. (2023) proposed SILO, a framework that utilizes a nonparametric datastore containing high-legal-risk data. However, the SILO framework does not address the risks associated with retrieval augmented generation (Wei et al., 2024), nor does it adequately address the practical challenges of ensuring that the training data for parametric models is limited to permissive content.

Machine Unlearning Machine Unlearning (Cao and Yang, 2015) have been proposed for LLMs to remove harmful knowledge (Liu et al., 2024e; Yao et al., 2023), private information (Dong et al., 2024), and copyrighted content (Jang et al., 2022; Eldan and Russinovich, 2023; Liu et al., 2024c). Additionally, Maini et al. (2024) and Yao et al. (2024) explored the *right to be forgotten* and introduced benchmarks for evaluating the unlearning effectiveness of private data. Li et al. (2024) further introduced a benchmark for forgetting hazardous knowledge in LLMs. However, none of these works have addressed the unlearning of copyrighted literary works in a sequential setting, nor the limitations of existing methods in this context.

Model Editing A related but distinct process is model editing (Meng et al., 2022; Hewitt et al., 2024; Gupta et al., 2024b). While unlearning aims to erase specific information from a model, model editing focuses on correcting errors without removing the underlying learned information (Liu et al., 2024d). Recent studies have shown that model editing in sequential settings can lead to model collapse (Gupta et al., 2024a; Yang et al., 2024a), and potential solutions have been proposed to mitigate this issue (Gupta and Anumanchipalli, 2024).

3 Preliminaries

3.1 Machine Unlearning for LLMs

Consider the original model and its weights, denoted as θ_o. Machine unlearning involves the problem where, given a dataset $D = \{(x_i, y_i)\}_{i=1}^N$ that θ_o was trained on, we aim to intentionally forget a subset of data, denoted as D_f, to obtain a modified model, denoted as θ_u, such that θ_u behaves as if it has never seen D_f during pre-training.

In the context of machine unlearning, we often use a retrained model excluding D_f during pre-training as a gold baseline. However, retraining a model for LLMs is extremely expensive and impractical in real-world settings.

3.2 Task Arithmetic

Unlearning via negating *task vectors* has recently gained attention (Ilharco et al., 2022; Liu et al., 2024e) and has become an important baseline approach for many unlearning tasks. The rationale behind this approach is that by negating the gradient updates of the unwanted data, we can achieve a more localized unlearning algorithm to effectively erase D_f from θ_o.

Specifically, the process involves two stages. First, we perform standard gradient descent to fine-tune θ_o on D_f, resulting in θ_{ft}. Next, we calculate the task vector as the element-wise difference $\theta_{ft} - \theta_o$. We then negate this task vector from θ_o to derive the unlearned model θ_u, expressed as $\theta_u = \theta_o - (\theta_{ft} - \theta_o)$.

3.3 Unlearning with Multiple Time Steps

We formally define sequential unlearning as the process where a model, originally trained on a dataset D, is incrementally modified to forget subsets of data at multiple time steps while preserving knowledge from the remaining data. Let D be the original dataset, and let $D_f^t \subseteq D$ denote the subset of data that must be forgotten at time step t, where $t = 1, 2, \dots, T$. The cumulative set of all data to be forgotten over time is defined as: $D_f = \cup_{t=1}^T D_f^t$. Let D_r represent the subset of data to be retained, such that $D_r = D \setminus D_f$, $D_f \cap D_r = \emptyset$, and $D_f \cup D_r = D$.

At each time step t, the unlearning process modifies the model to forget the subset D_f^t, resulting in a sequence of models $\{\theta_u^1, \theta_u^2, \dots, \theta_u^T\}$. Each θ_u^t is the model obtained after unlearning the data subsets $D_f^1, D_f^2, \dots, D_f^t$ sequentially. Formally, the goal of sequential unlearning is to ensure that after each unlearning step, the model θ_u^t minimizes the influence of D_f^t while retaining as much general-purpose knowledge from D_r as possible.

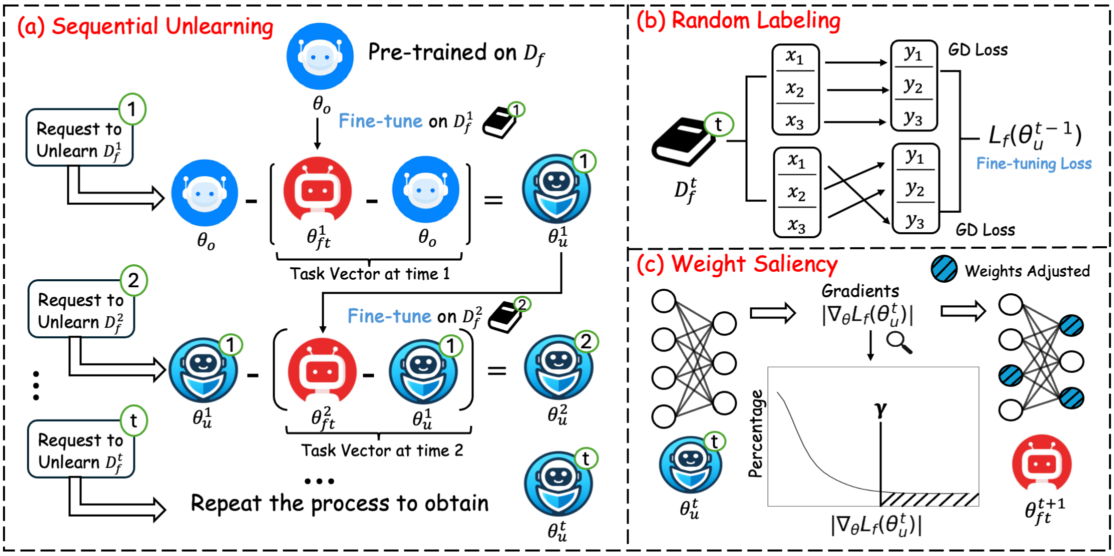


Figure 2: **Overall process of our unlearning framework.** **(a)** At each time step t, an unlearning request is received to forget the dataset D_f^t. The unlearning algorithm involves first fine-tuning θ_u^{t-1} on D_f^t to obtain θ_{ft}^t, and then subtracting the task vector from previously unlearned model θ_u^{t-1}. **(b)** At each time step t. we compute the gradient loss and random labeling loss to obtain the objective $L_f(\theta_u^{t-1})$ that will be used for fine-tuning. **(c)** At time step $t+1$, we fine-tune θ_u^t using the objective we obtained in (b), and only update model weights that are most salient using weight saliency mapping.

4 Methods

This section presents SSU, which leverages task vectors, incorporates additional loss term for ensuring unlearning efficacy and uses a gradient-based weight saliency map to ensure general-purpose language abilities. The overall process is shown in Figure 2. We first explain unlearning at each time step in section 4.1, and then generalize it to sequential setting in section 4.2.

4.1 Learning Stable Task Vectors

First, we present the case of unlearning during the first time step. This means that $t = 1$, $D_f^1 = D_f$, and $\theta_u^0 = \theta_o$. Following the intuition from task vectors, we first need to fine-tune a model on D_f. To do this, we define $h_\theta(x, y_{y<i}) = \mathbb{P}(y_i|(x, y_{<i}); \theta)$, which is the probability of the token y_i conditioned on the prompt x and the already generated tokens $y_{<i} = [y_1, y_2, ..., y_{i-1}]$. Next, we define the LLM's loss on y as:

$$L(x, y; \theta) := \sum_{i=1}^{|y|} \ell(h_\theta(x, y_{<i}), y_i), \qquad (1)$$

in which l is the cross-entropy loss.

Suppose θ_t is the current LLM through unlearning process. The first goal is to obtain a model that forgets D_f. Specifically, we define our first gradient descent loss term as:

$$\mathcal{L}_{\text{fgt}} = \sum_{(x_{\text{fgt}}, y_{\text{fgt}}) \in D_f} L(x_{\text{fgt}}, y_{\text{fgt}}, \theta_o). \qquad (2)$$

Random Labeling Loss Inspired by previous works demonstrating that injecting noise during training improves learning outcomes (Miyato et al., 2016; Srivastava et al., 2014; Neelakantan et al., 2015), we propose enhancing the effectiveness of unlearning by introducing data augmentation. Specifically, as shown in Figure 2 (b), we randomly mismatch the outputs of D_f with the inputs of D_f. During the first stage of the task vector approach, we include the following loss:

$$\mathcal{L}_{\text{rnd}} := \sum_{(x_{\text{fgt}},) \in D_f} \frac{1}{|D_f|} \sum_{(, y_{\text{rnd}}) \in D_f} L(x_{\text{fgt}}, y_{\text{rnd}}, \theta_t), \qquad (3)$$

in which y_{rnd} is any output from D_f and not corresponds to x_{fgt}.

By incorporating this random labeling loss, we introduce controlled noise into the unlearning process. This helps to prevent "overfitting" and enhance the stability of unlearning. Combining two loss terms, the final objective can be expressed as:

$$L_f(\theta_t) = \epsilon_1 \mathcal{L}_{\text{fgt}} + \epsilon_2 \mathcal{L}_{\text{rnd}}. \qquad (4)$$

Weight Saliency While performing sequential unlearning, we implicitly leverage the knowledge of previous steps. Specifically, as new requests are introduced, the most recent unlearning step adjusts the model weights based on the parameters from earlier unlearning steps. One of the main challenges with existing methods is that they often fail to control the changes in model weights during this process, which can lead to instability and faster degradation of the model's general-purpose capabilities.

Therefore, to preserve general-purpose language abilities, we should mitigate the risk of catastrophic collapse during each time step of sequential unlearning. We can achieve this by steering the unlearning process towards specific parts of the model weights that are most relevant to the data to be forgotten.

As shown in Figure 2 (c), we use a gradient-baased weight saliency map (Fan et al., 2023) during the first stage of fine-tuning to further ensure localized unlearning by only adjusting specific weights that are most influenced by the data to be forgotten. The weight saliency map is defined as:

$$m_s = \mathbb{1}(|\nabla_\theta L_f(\theta_t)| \geq \gamma), \quad (5)$$

in which $\mathbb{1}(f \geq \gamma)$ is an element-wise indicator function which outputs one for the i-th element if $f_i \geq \gamma$, and 0 otherwise, and $\nabla_\theta L_f(\theta_t)$ is a gradient vector.

Next, we apply the weight saliency mapping on the parameters that are most salient to unlearning and have the learned model as at each gradient accumulation step as:

$$\theta_{t+1} = m_s \odot (\Delta\theta + \theta_t) + (1 - m_s) \odot \theta_t, \quad (6)$$

where $\Delta\theta$ indicates model updates. After training for T gradient accumulation steps using Equation 6, we obtain a fine-tuned model θ^1_{ft}. Finally, we obtain our modified model using task vector by negating the knowledge of D_f learned during the fine-tuning process from the original model as:

$$\theta^1_u = \theta_o - (\theta^1_{ft} - \theta_o). \quad (7)$$

4.2 Sequential Unlearning

In this section, we explain how we generalize unlearning to sequential setting. As shown in Figure 2, at each new time step t, we have the previously unlearned model θ^{t-1}_u. Once we receive a new unlearning request, we will fine-tune θ^{t-1}_u using equation 6 as discussed in section 4.1 and obtain θ^t_{ft}. Lastly, we obtain a new unlearned model at time step t as:

$$\theta^t_u = \theta^{t-1}_u - (\theta^t_{ft} - \theta^{t-1}_u). \quad (8)$$

If more unlearning requests are received, we will iteratively apply the same process to obtain a newer unlearned model. Notably, unlike Gradient Difference, SSU does not require any additional retained dataset when calculating equation 4, ensuring efficiency and simplicity in real-world applications.

5 Experimental Setup

In this paper, we choose the removal of copyrighted books from LLMs as a representative scenario for authors to exercise their *intellectual property rights*. Machine unlearning can be applied to these LLMs to unlearn these books, thereby preventing the generation of verbatim copyrighted content.

5.1 Setting

We aim to evaluate the effectiveness of sequential unlearning of copyrighted books. At each time step, we unlearn one book following the experimental design of (Zhou et al., 2023; Carlini et al., 2022). For each book, we split the text into chunks of 200 tokens and use the system prompt, instruction prompt, and the first 100 tokens as prompt text to ask the model to continue the story, with the following 100 tokens serving as the ground truth. To assess the amount of copyrighted information being leaked, we compared the LLM's completion with the remaining 100 tokens of each chunk from the original book using techniques for extract training data proposed by Yu et al. (2023). Specifically, we use nucleus sampling (Holtzman et al., 2019) by setting the temperature to be 0.4 and $\eta = 0.6$, which means that the smallest set of the most likely tokens with total probabilities equal to or greater than 0.6 are selected.

In addition to books in D_f, we evaluate performance on previously unlearned books (D_{prev}, when $t > 1$) and books that should not be unlearned, denoted as D_{nor} (representing non-targeted knowledge), where $D_{nor} \subset D_r$. Details about experiment settings are in Appendix A.1.

5.2 Evaluation Metrics

To assess the effectiveness of copyright takedown methods in reducing copyright risks, we assess the transformativeness of the generated outputs in comparison to the original continuations (Henderson et al., 2023). Following Wei et al. (2024), we use Rouge-1 and Rouge-L scores (Lin, 2004) to measure the similarities between the model's outputs and the original content. For the books we aim to unlearn, lower Rouge-1 and Rouge-L scores indicate greater transformativeness, thereby reducing the risk of copyright infringement. In our experiments, we evaluated Rouge-1 and Rouge-L scores on the datasets D_f, D_{prev}, and D_{nor}. [4]

In addition to evaluating the model's unlearning effectiveness, we also assessed general-purpose language abilities after copyright takedown methods. The tasks considered include Massive Multitask Language Understanding (MMLU) (Hendrycks et al., 2020) and MT-Bench (Zheng et al., 2023). More details are in Appendix A.2.

5.3 Datasets and Models

We use the open-source language models Llama-3.1-8B-Instruct (Llama3.1) (Dubey et al., 2024) and Mistral-7B-Instruct-v0.3 (Mistral-7B) (Jiang et al., 2023), both fine-tuned on a dataset of 10 books from Project Gutenberg [5] (D_f) for one epoch as the vanilla models for our experiments.

For Llama-3.1, we unlearned 10 books across 10 time steps, and for Mistral-7B, we unlearned the first six books as many methods collapsed by time step 6 (see Figure 9). We intentionally selected The Adventures of Sherlock Holmes by Arthur Conan Doyle, *Pride and Prejudice* by Jane Austen, and *Alice's Adventures in Wonderland* by Lewis Carroll at the first, fifth, and eighth time steps, as these books are listed in Project Gutenberg's "Top 100 EBooks of the Last 30 Days." The remaining books were randomly sampled. All books were pre-processed following the methodology of Gerlach and Font-Clos (2020). At $t > 1$, we constructed D_{prev} by aggregating all previously unlearned books. Additionally, we selected 200 text chunks from 100 other books in Project Gutenberg, pre-processed as above, to form the D_{nor}. Further details are provided in Appendix A.3.

5.4 Baseline Methods

Following Wei et al. (2024), we compared our approach with several baseline methods:

[4]In alignment with previous copyright evaluation metrics (Maini et al., 2024; Yao et al., 2024), and recognizing that semantic similarity alone is insufficient to determine copyright infringement, we include evaluation metrics that focus on lexical similarity (e.g., Rouge) and exclude those that solely reflect semantic similarity.

[5]gutenberg.org

System prompts Following Wei et al. (2024), we use two system prompts to directly instruct the model to refrain from generating copyrighted content. The first, denoted as Prompting (a), adds instructions to not generate copyrighted contents to the default system prompt . The second, denoted as Prompting (dbrx), is used by the DBRX model from Databricks (Team et al., 2024). This prompt specifies that the model was not trained on copyrighted books. It explicitly mentions that the model does not provide such content (More details can be found in Appendix A.1).

MemFree Decoding The Memfree decoding checks whether the model's next token would create an n-gram found in the Bloom filter (Bloom, 1970). If it would, we will choose the next most probable token and do the check again, until the generated n-gram will not be found by the filter.

Unlearning Methods Unlearning methods such as Gradient Difference involves using books not in D_f to maintain performance and a random mismatch loss to force random outputs for unlearned data. NPO treats D_f as dispreferred data and formulates the unlearning problem within a preference optimization framework. More details, including hyperparameter choices, are in Appendix A.4.

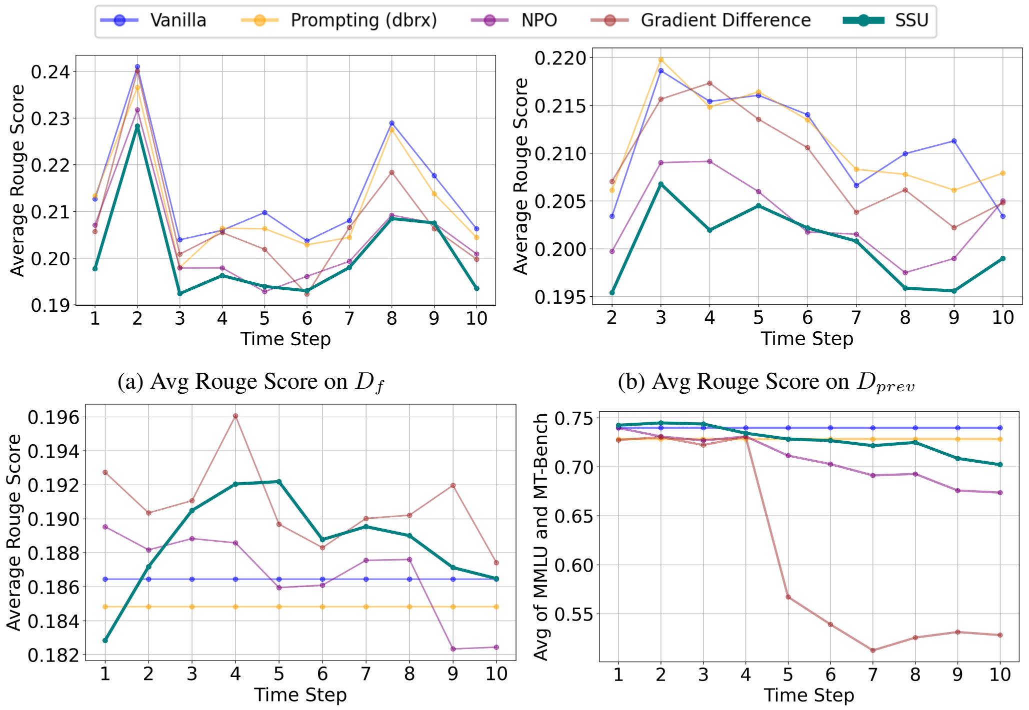
6 Results

We present experimental results of Llama3.1 for different unlearning time steps in Figure 3 and 6. See the results for Mistral-7B in Appendix C, and the results with exact numbers in Appendix D.

6.1 Sequential Unlearning of Books

This section examines the impact of unlearning on D_f and D_{prev}. Ideally, the model should have lower average Rouge scores to demonstrate lower risks of copyright infringement.

SSU consistently ranks among the top unlearning methods for mitigating copyright infringement. As shown in Figure 3a and 6a, for Llama3.1, SSU consistently achieves one of the lowest average Rouge scores on D_f. Similarly, as shown in Figure 3b and 6b, SSU proves to be one of the most effective across all time steps for books in D_{prev}, more effective in mitigating copyright infringement than NPO and Gradient Difference. The results are similar for Mistral-7B. As shown in Figures 9a and 9b, Gradient Ascent and Gradient Difference achieve the lowest Rouge scores



(a) Avg Rouge Score on D_f

(b) Avg Rouge Score on D_{prev}

(c) Avg Rouge Score on D_{nor}

(d) Avg MMLU and MT-Bench score

Figure 3: The averaged Rouge-1 and Rouge-L scores and benchmark scores for Llama3.1, omitting baseline methods that either consistently have low unlearning efficacy or easy to collapse (collapse details in Appendix D): (a) books to forget D_f (↓); (b) previously unlearned books D_{prev} (↓); (c) D_{nor} (↑). and (d) averaged normalized MMLU and MT-Bench scores (↑). Lower Rouge scores on D_f and D_{prev} indicate better unlearning, while higher scores for D_{nor} and benchmarks reflect better performance. Result with all methods is in Figure 6 in Appendix C.

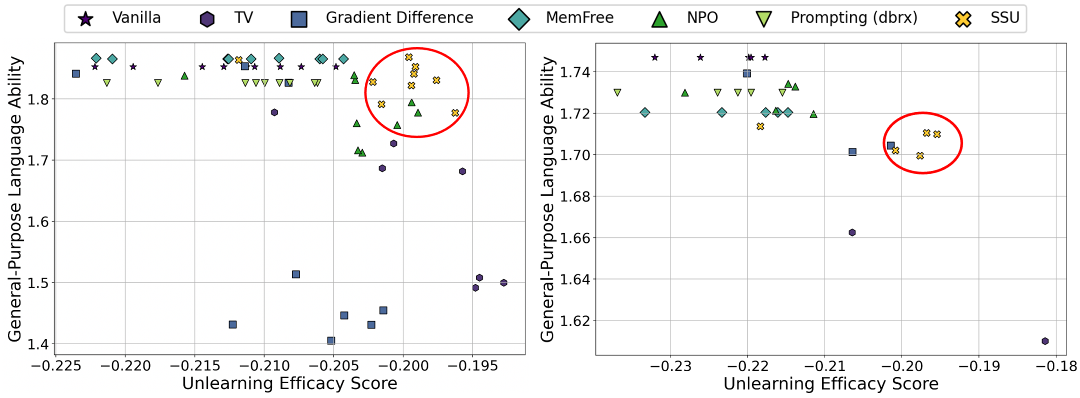
on D_f at later time steps, effectively erasing copyrighted content through opposite gradient updates, ultimately leading to catastrophic collapse. TV also maintains effective unlearning, but also collapses at time step 5. In contrast, NPO's average Rouge score on D_f remains close to the vanilla model, indicating ineffectiveness in mitigating copyright infringement. On the other hand, SSU demonstrates less risks of copyright infringement.

Prompting and MemFree Decoding offer limited mitigation of copyright infringement. As shown in Figures 6a and 9a, the Rouge scores for prompting and MemFree are largely indistinguishable from the vanilla model across many time steps and models. Although system prompts attempt to prevent generating copyrighted content, Llama3.1 often produces higher Rouge scores with prompting (a), and prompting (dbrx) is only marginally effective at certain time steps. We suspect this is due to the instruction-tuned Llama3.1 model's inability to differentiate what constitutes copyrighted content. For the Mistral-7B model, both prompting methods are similarly ineffective in reducing infringement risks. Lastly, the MemFree decoding is always ineffective in unlearning copyrighted books for for Llama3.1 and Mistral-7B.

6.2 Non-Targeted Knowledge Retention

This section examines the impact of unlearning on D_{nor}, the books not intended to be unlearned. Ideally, the model should maintain the average Rouge scores compared to the vanilla model.

SSU maximally preserves non-targeted knowledge compared to other unlearning methods. The results for Llama3.1 and Mistral-7B are notably different. For Mistral-7B, as shown in Figure 9c, the average Rouge scores for GA, Gradient Difference, and TV demonstrate significant loss of retained knowledge at later time steps. While NPO is less effective at mitigating copyright infringement, it consistently retains more knowledge of non-targeted books than SSU. In contrast, the results for Llama3.1 fluctuate. As shown in Figures 3c and 6c, Gradient Difference and SSU retain more knowledge of D_{nor} than the vanilla model. The unexpected re-emergence of these knowledge after unlearning is possibly due to knowledge redistribution during the unlearning process. Yang et al. (2024b) also examined this anticipatory recovery behavior where LLMs recover knowledge from



(a) Llama3.1-8B-Instruct Trade-off

(b) Mistral-7B-Instruct Trade-off

Figure 4: Trade-off analysis between general-purpose language abilities and unlearning efficacy for Llama3.1 and Mistral-7B, considering only methods at time steps greater than 1. For improved visualization, we exclude Prompting (a) and GA, which consistently exhibit low unlearning efficacy or collapse during the process. We also exclude TV beyond time step 9 (Llama3.1) and time step 3 (Mistral-7B), as well as Gradient Difference beyond time step 4 (Mistral-7B), due to collapose at these stage (see Appendix D for collapse details). General-purpose abilities are calculated using normalized averages of MMLU and MT-Bench scores, while unlearning efficacy is represented by the average of Rouge-1 and Rouge-L scores on D_f (targeted data) and D_{prev} (previously unlearned data). Lower Rouge scores indicate better unlearning performance; hence, these values are negated for clarity. The ideal method balances both metrics and is positioned in the top-right corner. Full result with all methods is in Figure 10.

the forgetting on documents before encountering them again. Further research is needed to explore this phenomenon. Nevertheless, SSU demonstrates stability by preserving knowledge in D_{nor}.

Prompting and MemFree decoding maintain non-targeted knowledge retention. As shown in Figures 6c and 9c, prompting and MemFree consistently retain non-targeted knowledge. Notably, for Llama3.1, both prompting (a) and MemFree retain more knowledge than the vanilla model. In contrast, for Mistral-7B, both prompting methods and MemFree exhibit slightly lower levels of knowledge retention compared to the vanilla model.

6.3 General-purpose Language Abilities

GA, Gradient Difference, and TV experienced catastrophic collapse at later time steps. Figures 3d, 6d, and 9d, show that GA, Gradient Difference, and TV both have sudden significant degradation of general-purpose abilities at certain time steps. NPO consistently underperforms SSU for Llama3.1 outperforms for Mistral-7B. Prompting and MemFree maintain stable general-purpose language abilities, close to the vanilla model.

6.4 Copyright Takedown Trade-offs

We present the overall trade-off of each method in Figures 4a and 4b. The x-axis represents unlearning efficacy score, and the y-axis represents general-purpose language ability. An ideal copyright takedown method would aim for the top-right corner. Comparing to existing baseline methods across two different models, **SSU achieves a better trade-off between unlearning efficacy and general-purpose language abilities retention.**

7 Analysis

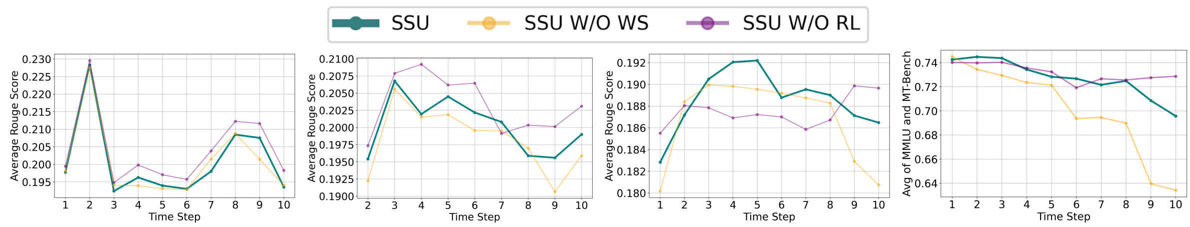
We analyze the impact of different components of SSU, including weight saliency maps and random labeling loss, on the sequential unlearning process. Figure 5 presents results for Llama3.1-8B-Instruct, and Figure 11 shows ablation results for Mistral-7B-Instruct-v0.3. We further present the effect of varying ϵ_1 and ϵ_2 in equation 4 in appendix B.1.

7.1 Impact of Weight Saliency

As shown in Figures 5a and 5b, the performance of SSU without weight saliency leads to lower average Rouge scores on both D_f and D_{nor}. Additionally, Figure 5d shows a sharper decline in benchmark performance with each time step, indicating that without weight saliency, the risk of catastrophic collapse increases as general-purpose language abilities deteriorate. **By updating only specific parts of the model's weights, weight saliency helps preserve the general-purpose language abilities.**

7.2 Impact of Random Labeling Loss

As seen in Figures 5a and 5b, SSU without random labeling loss results in a higher average Rouge scores and slightly improved general-purpose language abilities. This suggests that **random label-**



(a) Avg Rouge on D_f (b) Avg Rouge Score on D_{prev} (c) Avg Rouge Score on D_n (d) General Performance

Figure 5: Ablation study of SSU for Llama3.1-8B-Instruct. The orange line represents unlearning without the weight saliency map, while the purple line shows the effect of removing the random labeling loss.

ing loss enhances the model's ability to unlearn D_f consistently across all time steps.

It is also noteworthy that, as shown in Figures 5c and 11c, SSU without weight saliency and SSU without random loss lead to lower average Rouge scores for D_{nor} in both models. This observation highlights the need for further research on the impact of unlearning algorithms on preserving content not intended for unlearning.

8 Conclusion

We explore sequential unlearning of copyrighted content in LLMs to mitigate copyright infringement. We propose SSU, which utilizes random labeling loss and gradient-based weight saliency to achieve more stable sequential unlearning. Experiments show SSU outperforms existing methods in balancing unlearning efficacy and language retention. Future research could focus on enhancing the robustness of unlearning algorithms and exploring other copyright takedown methods to further mitigate the risks of copyright infringement.

Limitations

Robustness of Machine Unlearning Our evaluation relies on lexical-based metrics, which, as noted by Ippolito et al. (2023), may provide a false sense of privacy. Additionally, Łucki et al. (2024) and Cooper et al. (2024) highlight that existing unlearning methods often lack robustness and may merely obscure data rather than true unlearning.

In our experiments, we observe that knowledge from previously unlearned books can re-emerge at certain future time steps, a phenomenon present across all unlearning algorithms tested (see Appendix B.2). This further underscores the challenges of sequential unlearning and the necessity for more robust unlearning algorithms.

Unintended Knowledge and Capability Loss While SSU achieves a better trade-off between unlearning efficacy and general-purpose language retention, it still weakens the model's reasoning and conversational abilities. Future work should further reduce this gap, ensuring better preservation of general knowledge during sequential unlearning.

Unlearning Is Not All You Need Mitigating copyright infringement risks requires more than unlearning alone. For example, Liu et al. (2024a) introduces Infini-gram, an efficient search engine for scanning large-scale LLM training corpora. A complementary approach could involve using such tools to detect copyrighted passages in generated outputs and intervene to ensure non-copyrighted regeneration. This generation-time copyright takedown method represents a promising research direction. Future work could expand search engine tools to cover a broader range of training datasets used in state-of-the-art LLMs. Additionally, regularly updating model checkpoints to align with *the right to be forgotten* would be crucial for maintaining legal and ethical compliance.

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A Experiment Details

A.1 Experiment Settings

To evaluate the effectiveness of sequential unlearning, we conduct experiments on several copyrighted books. Our process involves the following steps:

First, each book is split into many chunks of 200 tokens. For each chunk, the initial 100 tokens are used as a prompt, which is fed into the LLM. The remaining 100 tokens serve as the answer or continuation from the original book. This setup allows us to assess how well the model can generate text that follows the given prompt.

In addition to the prompt from the book, we use a system prompt and a instruction prompt to guide the model in generating the completion.

The default system prompt is

> "You are a helpful, respectful and honest assistant."

and the default instruction prompt is

> "Please complete the rest of the following paragraph based on the context."

For each prompt, the model generates a completion using a nucleus sampling by setting the temperature to 0.4 and $\eta = 0.6$. This follows bags of tricks to extract training data suggested by Yu et al. (2023).

To evaluate the generated completions and its risk of copyright infringement, we use Rouge-1 and ROUGE-L score. These metrics allow us to compare the LLM's completions with the original text and assess the model's ability to unlearn specific content.

Specifically, we evaluate the scores on the following sets of books:

- Books to be forgotten (D_f)
- Books that are previously unlearned when time step is greater than one (D_{prev})
- Books that not to be forgotten (D_{nor})

In subsequent sections, we refer to the performance on D_{nor} as knowledge retention.

Additionally, following the setup of Wei et al. (2024), we evaluate the model's performance on general reasoning tasks to assess its capability retention. The downstream tasks considered include 5-shot Massive Multitask Language Understanding (MMLU) (Hendrycks et al., 2020), and MT-Bench (Zheng et al., 2023).

A.2 Evaluation Metrics

A.2.1 Rouge-1

Recall-Oriented Understudy for Gisting Evaluation (Rouge) includes Rouge-1, which measures the overlap of unigram (single word) occurrences between the LLM's completion and the original books. A unigram is any individual word that appears in both the completion (hypothesis text) and the original book (reference text).

First, we define the recall as the ratio of the number of overlapping unigrams between the hypothesis and reference text to the total number of unigrams in the reference text:

$$Recall = \frac{\text{overlapping unigrams}}{\text{total unigrams in the reference}}.$$

Similarly, precision is defined as the ratio of the number of overlapping unigrams to the total number of unigrams in the hypothesis text:

$$Precision = \frac{\text{overlapping unigrams}}{\text{total unigrams in the hypothesis}}.$$

Lastly, the Rouge-1 score used in our experiments is calculated as the F1 score, which combines precision and recall:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

A.2.2 Rouge-L

Rouge-L measures the longest common subsequence (LCS) between the LLM's completion and original books. In detail, LCS is a sequence that appears in both the completion (hypothesis text) and original book (reference text) in the same order but not necessarily contiguously.

Next, we define the recall as the ratio of the length of the LCS to the total length of the reference text:

$$Recall = \frac{LCS}{\text{length of the reference text}}.$$

We also define the precision as the ratio of the length of the LCS to the total length of the hypothesis text:

$$Precision = \frac{LCS}{\text{length of the hypothesis text}}.$$

Lastly, the Rouge-L score we used in our experiments is defined as:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

A.3 Datasets

This section provides detailed information about the books used in the experiment. We crawled all available books from Project Gutenberg[6] and pre-processed them following the methodology of Gerlach and Font-Clos (2020), in which we remove all headers and boiler plate text.

A.3.1 Books to Forget

At time step 1, we unlearn The Adventures of Sherlock Holmes by Arthur Conan Doyle. At time step 2, we unlearn Flowers of the Sky by Richard A. Proctor, Pagan Papers by Kenneth Grahame at time step 3, Diary of Samuel Pepys by Samuel Pepys at time step 4, Pride and Prejudice by Jane Austen at time step 5, They Call Me Carpenter: A Tale of the Second Coming by Upton Sinclair at time step 6, Memoirs of the Court of Louis XIV. and of the Regency — Complete by Orléans at time step 7, Alice's Adventures in Wonderland by Lewis Carroll at time step 8, The Wonderful Adventures of Nils by Selma Lagerlöf at time step 9, and Starr, of the Desert by B. M. Bower at time step 10.

For the books in D_f, the entire texts are split into chunks of 200 tokens, and the dataset is formatted as question-answer pairs, where the first 100 tokens represent the Question, and the subsequent 100 tokens represent the Answer. All texts from each book are included and formatted into JSON files.

At each time step greater than one, we form D_{prev} by collecting all the books that we have unlearned since the first time step. Specifically, we then split all of the books that are used in previous unlearning steps into chunks of 200 tokens to form many QA pairs, and then randomly sampled 200 such pairs to form D_{prev}.

A.3.2 Books in D_{nor}

To evaluate the model's knowledge retention after unlearning, we constructed a set of books that we do not want the model to forget. Specifically, we randomly sampled 100 books from Project Gutenberg that are not included in D_f. Following the same preprocessing steps used for D_f, we split these books into chunks of 200 tokens, and randomly sampled 200 chunks to form the dataset D_{nor}. Since the books in D_{nor} are not part of D_f at any time step, the content of D_{nor} remains unchanged throughout the experiment.

[6]gutenberg.org

A.4 Baseline Methods

A.4.1 Generic Prevention using System Prompt

The default system prompts being used for all the unlearning and MemFree decoding methods have been described in Appendix A.1. Here, we present two copyright takedown methods using well crafted system prompts.

First, we denote our baseline method Prompt (a) as using the system prompt:

> "You are a helpful, respectful and honest assistant. When generating your response, please do not generate the copyrighted content."

which adds a brief instruction to not generate copyrighted content after the default system prompt.

We also included Prompt (dbrx), which is a system prompt being used by the DBRX model, released by Databricks:

> "You are a helpful, respectful and honest assistant. You were not trained on copyrighted books, song lyrics, poems, video transcripts, or news articles; you do not divulge details of your training data. You do not provide song lyrics, poems, or news articles and instead refer the user to find them online or in a store."

A.4.2 MemFree Decoding

To prevent the model from emitting memorized content, we employed MemFree decoding (Ippolito et al., 2022). This method checks each n-gram during text generation to ensure it does not match any sequences from the training set. If a match is detected, the token is resampled, thereby avoiding verbatim reproduction of training data. The process is optimized through the use of Bloom filters, which allow for efficient real-time memorization checks. Although MemFree effectively stops exact memorization, it does not fully eliminate the risk of paraphrased or approximate memorization. We implemented MemFree based on Wei et al. (2024).

A.4.3 Unlearning via Gradient Difference

In this work, we use the method proposed by (Yao et al., 2023) as one of the baseline methods. Here we present the case of performing gradient difference unlearning.

Specifically, let θ to be the current LLM, let DD_f to be the dataset representing the book we want to forget, and D_{add} to a set of book corpora that does not contain the book to be forgotten, nor the books in D_{nor}. Moreover, we define $h_\theta(x, y_{y<i}) = \mathbb{P}(y_i|(x, y_{<i}); \theta)$, which is the probability of the token y_i conditioned on the prompt x and the already generated tokens $y_{<i} = [y_1, y_2, ..., y_{i-1}]$. Next, we define the LLM's loss on y as:

$$L(x, y; \theta) := \sum_{i=1}^{|y|} \ell(h_\theta(x, y_{<i}), y_i)$$

The Gradient Difference has three loss terms, defined as follows:

$$\mathcal{L}_{\text{fgt}} = -\sum_{(x_{\text{fgt}}, y_{\text{fgt}}) \in D_f} L(x_{\text{fgt}}, y_{\text{fgt}}, \theta_t)$$

$$\mathcal{L}_{\text{rnd}} := \sum_{(x_{\text{fgt}},) \in D_f} \frac{1}{|Y_{\text{rnd}}|} \sum_{(,y_{\text{rnd}}) \in Y_{\text{rnd}}} L(x_{\text{fgt}}, y_{\text{rnd}}, \theta_t)$$

$$\phi_\theta = h_\theta(x_{\text{nor}}, y_{\text{nor}<i})$$

$$\mathcal{L}_{\text{add}} := \sum_{(x_{\text{add}}, y_{\text{add}}) \in D_{\text{add}}} \sum_{i=1}^{|y_{\text{add}}|} \text{KL}(\phi_{\theta_o} \parallel \phi_{\theta_t}).$$

in which Y_{rnd} is a set of responses irrelevant to responses of D_f, sampled from D_{add}.

Lastly, the GA approach is trying to minimize the following loss to obtain the unlearned model:

$$L = \epsilon_1 \mathcal{L}_{\text{fgt}} + \epsilon_2 \mathcal{L}_{\text{rnd}} + \epsilon_3 \mathcal{L}_{\text{add}}$$

$$\theta_{t+1} \leftarrow \theta_t - \nabla L.$$

in which $\mathcal{L}_{\text{fgt}}$ is a gradient ascent loss on D_f, which tries to make the model perform poorly on the D_f. Next, $\mathcal{L}_{\text{rnd}}$ tries to randomly mismatch the labels from non-relevant dataset to the inputs of the dataset we want to forget. Lastly, $\mathcal{L}_{\text{add}}$ tries to maintain the performance on the normal dataset. In our experiment, we set $\epsilon_1 = 1$, $\epsilon_2 = \epsilon_3 = 0.5$ across all time steps and all models.

A.4.4 Unlearning via Task Vector

We also use the task vector method as one of the baseline approaches, which typically involves a two-stage process. Considering the case of $t = 1$, we denote θ_o as the original model weights. We intentionally fine-tune the model on D_f to obtain θ_{ft}^1. This fine-tuning process is defined as follows:

$$\mathcal{L}_{\text{fgt}} = \sum_{(x_{\text{fgt}}, y_{\text{fgt}}) \in D_f} L(x_{\text{fgt}}, y_{\text{fgt}}, \theta_t)$$

$$\theta_{t+1} \leftarrow \theta_t - \epsilon \nabla_{\theta_t} \mathcal{L}_{\text{fgt}}$$

Next, we define the task vector τ as the element-wise difference between θ_{ft} and θ_o:

$$\tau = \theta_{ft}^1 - \theta_o$$

Finally, the unlearned model θ_u at time step t is obtained by:

$$\theta_u^1 = \theta_o - \tau$$

The general intuition behind this method is to first obtain a model that is specialized in the dataset we aim to forget. The task vector τ represents the changes in weights required to acquire this specific knowledge. By subtracting these "knowledge" weights from the original model, we effectively unlearn the targeted information.

A.4.5 Unlearning via NPO

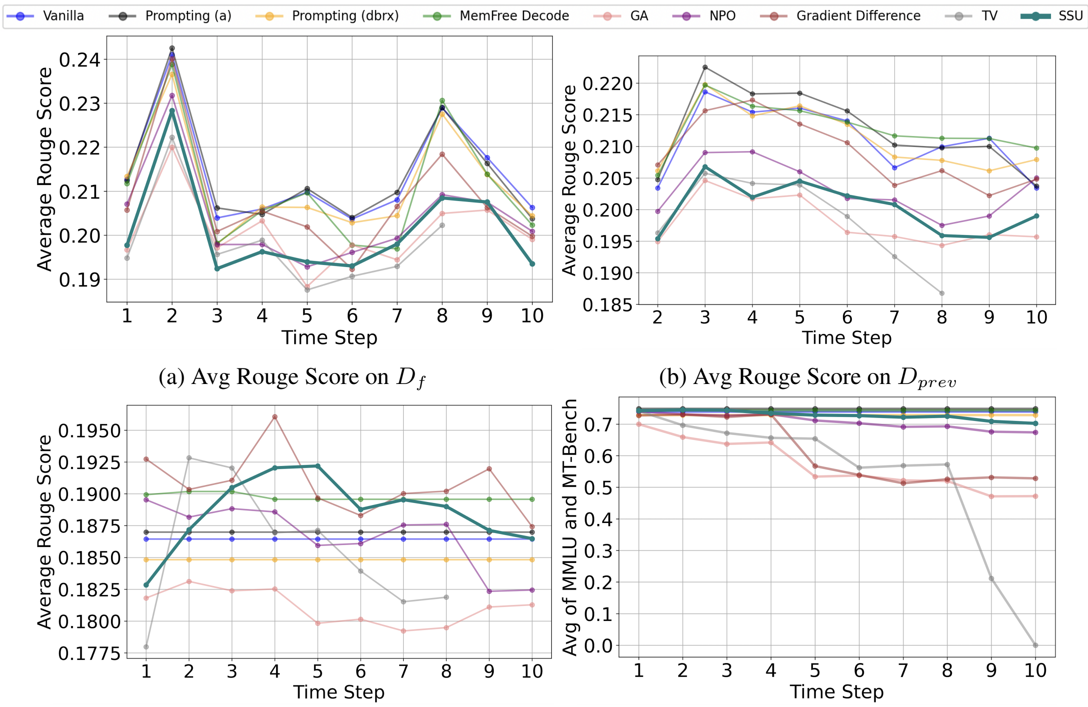
In this work, we utilize the Negative Preference Optimization (NPO) method for unlearning undesirable data, aiming to overcome the catastrophic collapse often observed with gradient ascent methods. NPO builds on the framework of preference optimization, specifically focusing on negative samples from the dataset to be unlearned.

The NPO loss function is defined as follows:

$$\mathcal{L}_{\text{NPO}} = \frac{2}{\beta} \mathbb{E}_{(x,y) \in D_{\text{f}}} \left[\log \left(1 + \left(\frac{\pi_\theta(y|x)}{\pi_{\text{ref}}(y|x)} \right)^\beta \right) \right]$$

where $\pi_\theta(y|x)$ represents the prediction probability of the current model for token y given the input x, and $\pi_{\text{ref}}(y|x)$ is the prediction probability from the reference model trained on the entire dataset. The parameter β controls the smoothness of the optimization, and as $\beta \to 0$, the NPO loss converges to the standard gradient ascent loss.

Minimizing this loss helps reduce the model's reliance on the forget set, ensuring that the unlearning process remains stable and avoids the rapid deterioration seen in gradient ascent approaches. In our experiment, we set $\beta = 0.4$, and we obtain π_{ref} by optimizing off-the-shelf LLMs on $D_f \bigcup D_{nor}$.



(a) Avg Rouge Score on D_f

(b) Avg Rouge Score on D_{prev}

(c) Avg Rouge Score on D_n

(d) Avg MMLU and MT-Bench score

Figure 6: The average of Rouge-1 and Rouge-l and benchmark scores for Llama3.1: (a) books to forget D_f (↓); (b) previously unlearned books D_{prev} (↓); (c) D_{nor} (↑). and (d) averaged normalized MMLU and MT-Bench scores (↑). The results for TV after time step 8 are omitted due to collapse. Lower Rouge scores for D_f and D_{prev} indicate better unlearning, while higher scores for D_{nor} and benchmarks reflect better performance.

A.5 Implementation Details

The experiments are conducted on eight RTX A6000 GPUs. For all unlearning algorithms, at each time step, we only unlearn the model for 1 epoch, with a batch size set to 2. During all the fine-tuning process, we used Lora (Hu et al., 2021), and we did not quantize the model because quantization leads to inaccurate element-wise subtraction for TV-based methods.

For the Llama-3.1-8B-Instruct model, we set the learning rate to be 1e-5 for the first five time steps, and decrease the learning rate to 1e-6 for the rest of the time steps. For the Mistral-7B-Instruct-v0.3, we set the learning rate to be 1e-5 for the first three time steps, and the learning rate to be 1e-6 for other time steps. For SSU, we set $\epsilon_1 = 1$,a and $\epsilon_2 = 0.5$ for all the time steps and models. We set γ to be 1 standard deviation away from the mean of the gradient vector $\nabla_\theta L_f(\theta_t)$

B Additional Analysis

B.1 Impact of ϵ_1 and ϵ_2

In this section, we analyze the impact of the hyperparameters ϵ_1 and ϵ_2 in Equation 4. Specifically, we denote $SSU_{1.5,1}$ as the method with $\epsilon_1 = 1.5$ and $\epsilon_2 = 1$ on Llama 3.1, and $SSU_{1,2}$ as the method with $\epsilon_1 = 1$ and $\epsilon_2 = 2$. All other hyperparameters remain consistent with the settings used in our main experiments.

As shown in Table 1, SSU maintains strong performance on MMLU and MT-Bench, indicating its stability across different parameter values. Unlike gradient ascent and gradient difference methods, SSU does not lead to model collapse. However, in our main experiments, we tuned ϵ_1 and ϵ_2 to achieve the best trade-off between unlearning efficacy and general-purpose language abilities.

B.2 Re-Emergence in Sequential Unlearning

In the main text, we use D_{prev} -the set of all previously unlearned books—to assess whether they remain unlearned throughout sequential unlearning. Here, instead of evaluating all unlearned books collectively, we examine how knowledge of each previously unlearned book evolves as new books are unlearned at later time steps.

Figures 7 and 8 present the results for Llama 3.1 and Mistral-7B, respectively. The x-axis denotes the number of unlearning steps performed, while

Time Step	Method	D_f	D_f	D_{prev}	D_{prev}	D_{nor}	D_{nor}	MMLU	MT-Bench
1	$SSU_{1.5,1}$	0.2513	0.1424	N/A	N/A	0.2307	0.1335	0.6631	8.1180
1	$SSU_{1,2}$	0.2515	0.1417	N/A	N/A	0.2316	0.1335	0.6624	7.8058
2	$SSU_{1.5,1}$	0.2856	0.1688	0.2558	0.1433	0.2402	0.1376	0.6463	8.1850
2	$SSU_{1,2}$	0.2852	0.1689	0.2567	0.1433	0.2393	0.1367	0.6470	8.1675
3	$SSU_{1.5,1}$	0.2415	0.1400	0.2699	0.1539	0.2403	0.1378	0.6463	7.9870
3	$SSU_{1,2}$	0.2414	0.1386	0.2704	0.1543	0.2394	0.1370	0.6466	8.1283
4	$SSU_{1.5,1}$	0.2492	0.1390	0.2576	0.1517	0.2458	0.1389	0.6431	8.0349
4	$SSU_{1,2}$	0.2420	0.1403	0.2565	0.1511	0.2439	0.1391	0.6431	8.0266
5	$SSU_{1.5,1}$	0.2551	0.1365	0.2650	0.1527	0.2441	0.1385	0.6298	7.9812
5	$SSU_{1,2}$	0.2545	0.1369	0.2640	0.1517	0.2429	0.1378	0.6319	8.0578
6	$SSU_{1.5,1}$	0.2494	0.1412	0.2621	0.1472	0.2435	0.1392	0.6298	7.9812
6	$SSU_{1,2}$	0.2476	0.1408	0.2632	0.1467	0.2433	0.1380	0.6263	8.0484

Table 1: Results across time steps with different ϵ. All performance metrics on D are reported as Rouge-L scores.

the y-axis represents the ROUGE-L score for each individual book. Notably, in certain future time steps, the ROUGE-L score of previously unlearned books increases. For instance, as shown in Figure 7d, the ROUGE-L score of the fourth book under NPO rises as the model unlearns additional books. Similar trends appear in Figure 7a, where NPO's score for the first book increases at time step 9, and in Figure 8a, where the Mistral model exhibits a steady increase in NPO's score as it unlearns other books over time.

We also observe instability in the gradient difference, particularly in Figure 7, where performance on previously unlearned books fluctuates significantly across future time steps. Additionally, SSU exhibits some degree of reappearance of previously unlearned knowledge. This aligns with Łucki et al. (2024), in which it pointed out that fine-tuning on data unrelated to D_f can inadvertently recover unlearned knowledge. Since all baselines in our experiments rely on fine-tuning with unlearning objectives, sequential unlearning fine-tunes the model on unrelated data—books unlearned at later time steps are independent of those unlearned earlier. This highlights a key challenge in sequential unlearning: continual model modifications may lead to knowledge re-emergence, highlighting the need for more robust unlearning algorithms in sequential settings.

C Full Experiment Results

Here we present the performance of SSU compared to all other baseline methods, using Llama3.1-8B-Instruct in Figure 6 and Mistral-7B-Instruct in Figure 9.

Additionally, we present trade-off comparisons of all the baseline methods except GA (GA is collapsed at most time steps in Mistral-7B-Instruct) in Figure 10. Moreover, the x-axis used in Figure 10 is defined as:

$$\text{Unlearning Efficacy} = U_f + U_{\text{prev}}$$

where

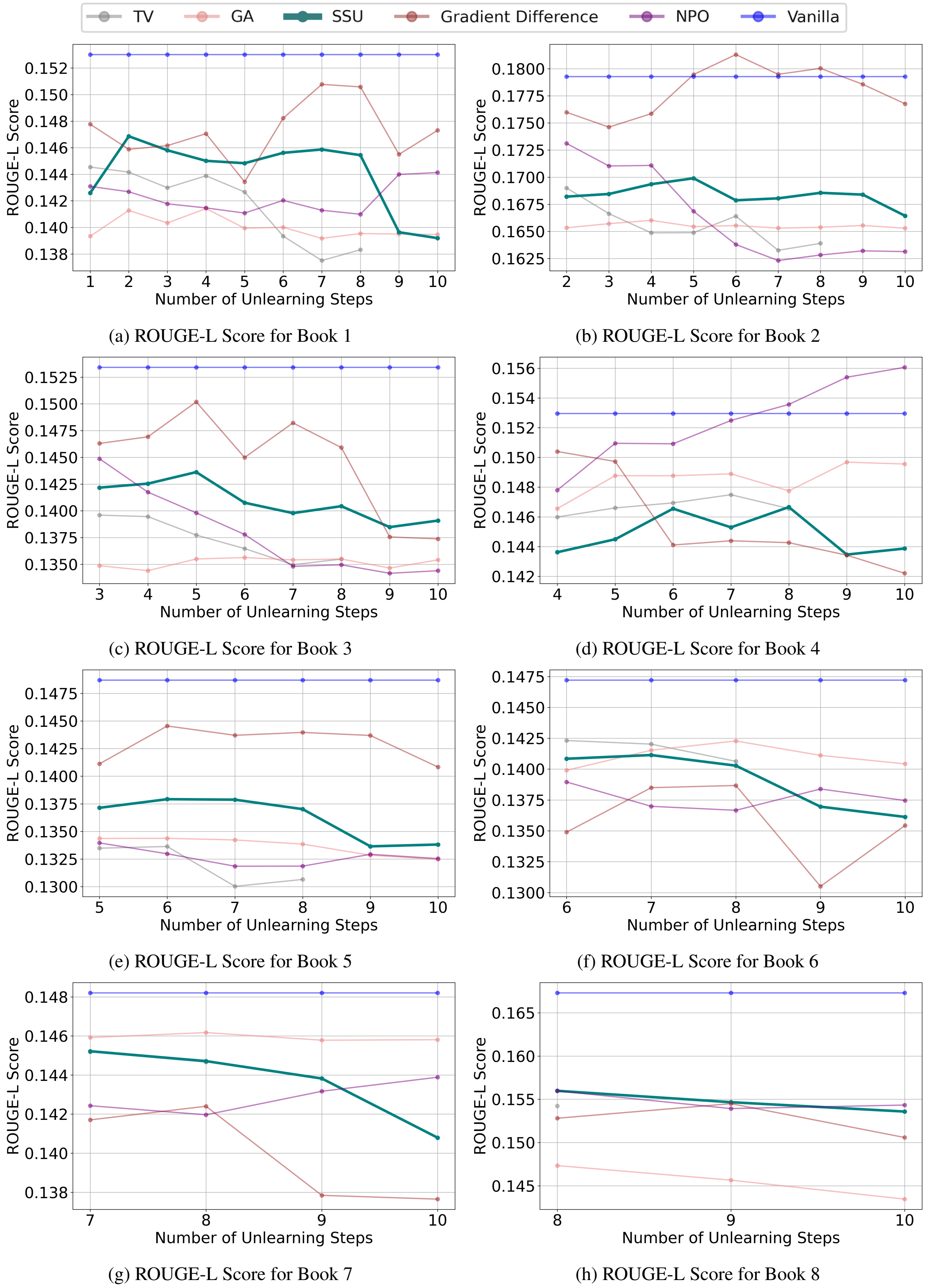
$$U_f = -\frac{1}{2}\left(R_1^f + R_L^f\right)$$

$$U_{\text{prev}} = -\frac{1}{2}\left(R_1^{\text{prev}} + R_L^{\text{prev}}\right).$$

Here, R_1^f and R_L^f represent the Rouge-1 and Rouge-L scores for D_f, and R_1^{prev} and R_L^{prev} represent the Rouge-1 and Rouge-L scores for D_{prev}. The y-axis (General-purpose Language Ability) is defined as:

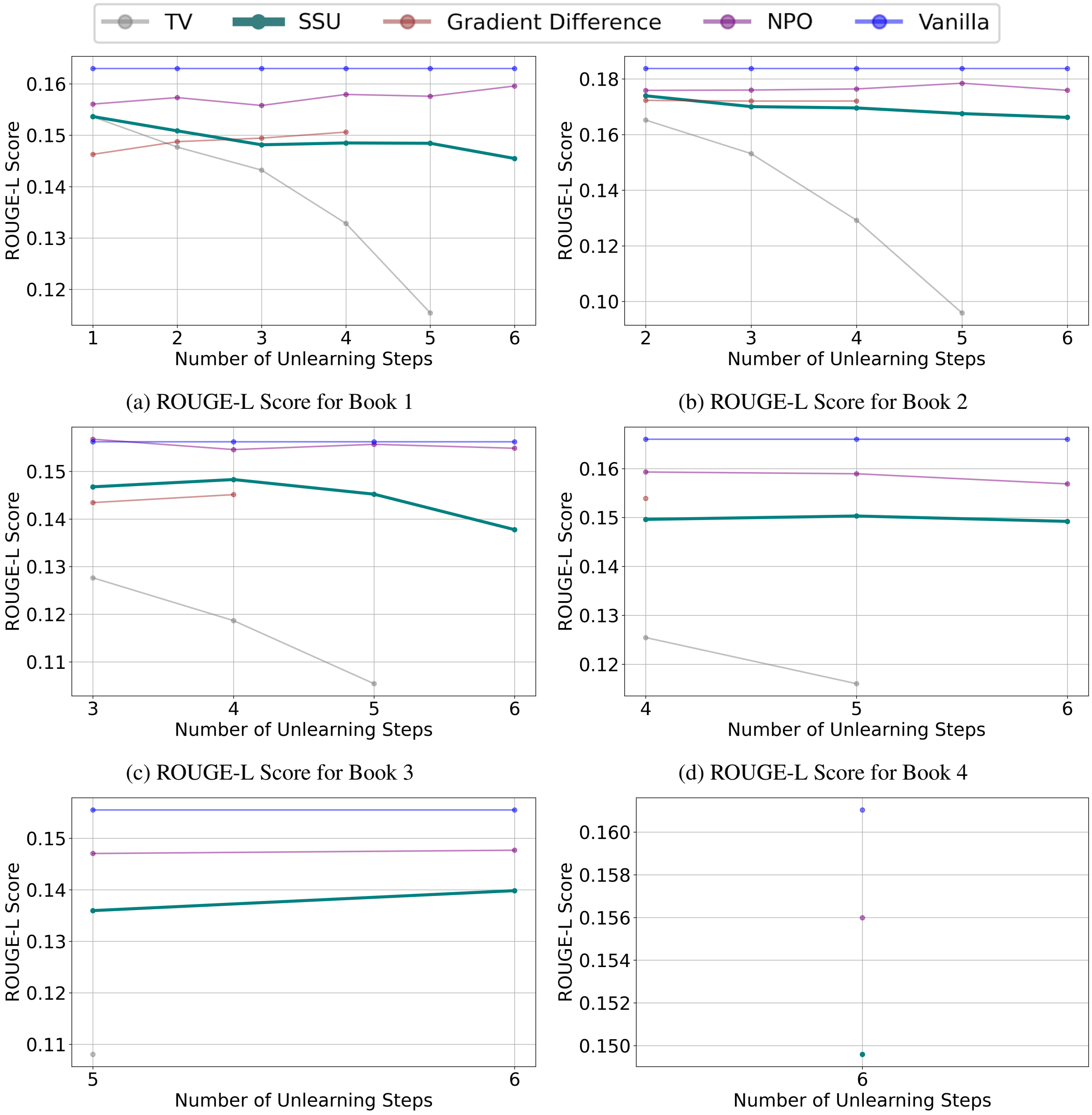
$$\frac{1}{2}\left(M + \frac{B}{10}\right)$$

where M and B represent the MMLU and MT-Bench scores, respectively. We also present the ablation study resuls for Mistral-7B-Instruct-v0.3 in Figure 11.



(a) ROUGE-L Score for Book 1
(b) ROUGE-L Score for Book 2
(c) ROUGE-L Score for Book 3
(d) ROUGE-L Score for Book 4
(e) ROUGE-L Score for Book 5
(f) ROUGE-L Score for Book 6
(g) ROUGE-L Score for Book 7
(h) ROUGE-L Score for Book 8

Figure 7: ROUGE-L score for each previously unlearned book, evaluated using various unlearning methods on the Llama 3.1. The x-axis represents the number of time steps (i.e., the number of sequential unlearning operations performed), while the y-axis indicates the ROUGE-L score. Different unlearning methods are compared, with 'Vanilla' serving as the baseline model without unlearning. We omit certain time steps for some methods because of the catastrophic collapse.



(a) ROUGE-L Score for Book 1

(b) ROUGE-L Score for Book 2

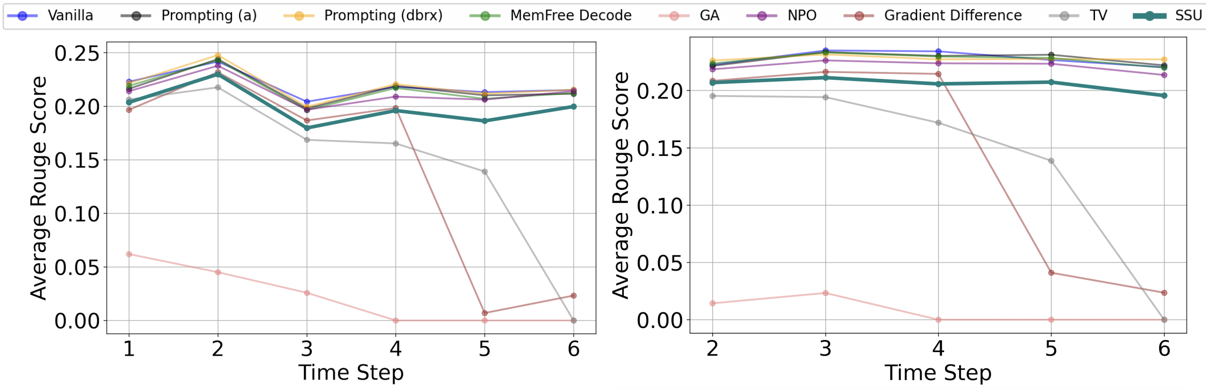
(c) ROUGE-L Score for Book 3

(d) ROUGE-L Score for Book 4

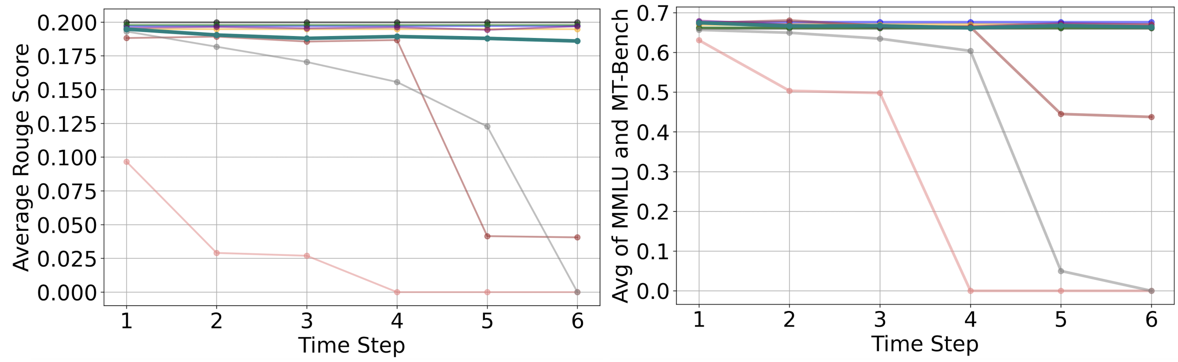
(e) ROUGE-L Score for Book 5

(f) ROUGE-L Score for Book 6

Figure 8: ROUGE-L score for each previously unlearned book, evaluated using various unlearning methods on the Mistral model. The x-axis represents the number of time steps (i.e., the number of sequential unlearning operations performed), while the y-axis indicates the ROUGE-L score. Different unlearning methods are compared, with 'Vanilla' serving as the baseline model without unlearning. We omit certain time steps for some methods because of the catastrophic collapse.

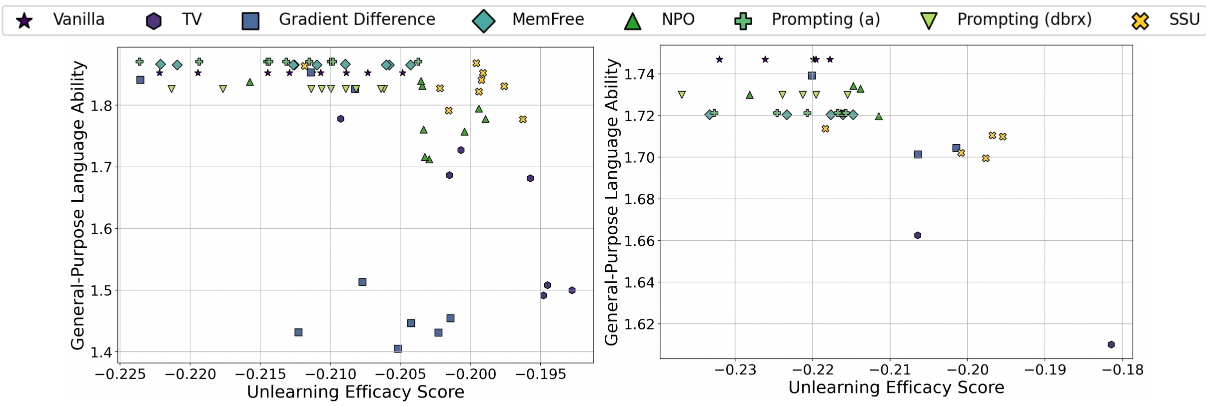


(a) Avg Rouge Score on D_f (b) Avg Rouge Score on D_{prev}



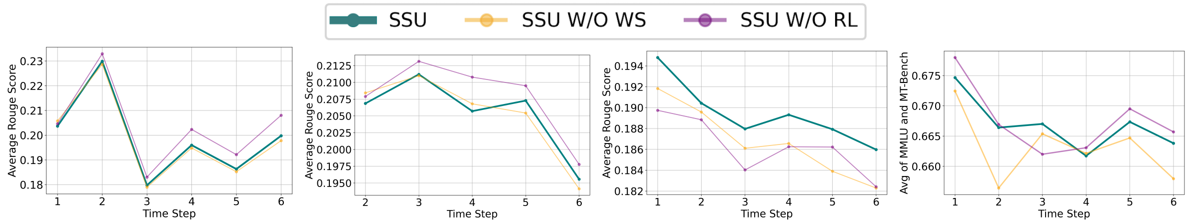
(c) Avg Rouge Score on D_n (d) Avg MMLU and MT-Bench score

Figure 9: The average of Rouge-1 and Rouge-l score and reasoning abilities for Mistral-7B-Instruct: (a) books to forget D_f (↓); (b) previously unlearned books D_{prev} (↓); (c) D_{nor} (↑). and (d) averaged normalized MMLU and MT-Bench scores (↑). The results for TV after time step 8 are omitted due to collapse. Lower Rouge scores for D_f and D_{prev} indicate better unlearning, while higher scores for D_{nor} and benchmarks reflect better performance.



(a) Llama3.1-8B-Instruct Trade-off (b) Mistral-7B-Instruct Trade-off

Figure 10: Trade-off between general-purpose language abilities and unlearning efficacy for Llama3.1 and Mistral-7B, including all methods, except TV beyond time step 9 (Llama3.1) and time step 3 (Mistral-7B), and Gradient Difference beyond time step 4 (Mistral-7B), as they all collapsed during these time steps. General-purpose abilities are represented by the average of MMLU and MT-Bench scores, normalized. Unlearning efficacy is measured as the average of Rouge-1 and Rouge-L scores on D_f and D_{prev}, where lower Rouge scores indicate better unlearning performance; thus, values were negated for clarity. The ideal performance is positioned in the top-right corner. The plots capture the performance of all methods at every time step greater than 1.



(a) Avg Rouge on D_f (b) Avg Rouge Score on D_{prev} (c) Avg Rouge Score on D_n (d) General Performance

Figure 11: Ablation study of SSU for Mistral-7B-Instruct-v0.3. The orange line represents unlearning without the weight saliency map, while the purple line shows the effect of removing the random labeling loss.

D Numeric Experiment Results

In this section, we present our experimental results numerically. Tables 2 to 11 display the unlearning results of Llama3.1 across all ten time steps. Tables 12 to 17 show the results for Mistral-7B unlearning across all six time steps. In sections D.1 and D.2 we illustrate how GA, TV, and Gradient Difference encounter catastrophic collapse.

D.1 Catastrophic Collapse of Llama3.1

GA, TV, and Gradient Difference experience varying levels of model collapse during the sequential unlearning process. As shown in table 2, GA begins with an MMLU of 0.5821. By time step 5, GA's MMLU has dropped to 0.3102 6, demonstrating a rapid degradation in general reasoning. Similarly, TV starts with an MMLU of 0.6621 at time step 1 and undergoes a steep decline in reasoning ability, dropping to 0.4887 by time step 5, and reaching an MMLU of 0 at time step 10 (as shown in tables 6 and 11). Additionally, Gradient Difference also faces catastrophic collapse at time step 5. Specifically, its MT-Bench score falls from 8.034 at time step 4 (table 5) to 4.9438 at time step 5, and further declines to 4.48 at time step 10, though its MMLU score remains stable. Lastly, NPO and SSU exhibit a gradual decline in general-purpose language abilities, but SSU consistently outperforms NPO across all the time steps.

D.2 Catastrophic Collapse of Mistral-7B

GA and TV experience rapid model collapse, while Gradient Difference still suffers loss of conversational ability. As shown in table 12, GA collapses at the first time step. TV initially declines gradually but undergoes a sudden reasoning degradation at time step 5 (table 15), where both MMLU and MT-Bench scores drop to 0. Gradient Difference experiences a sharp decrease in MT-Bench score from 7.2375 at time step 4 to 2.8375 at time step 5, eventually dropping to 2.6815 at time step 6. Similar to the Llama3.1 case, Gradient Difference maintains stable performance on MMLU. Lastly, NPO maintains competitive general-purpose abilities scores compared to SSU, Figures 9 and 10 show that SSU demonstrates superior unlearning efficacy and achieves a better trade-off.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2724	0.1530	0	0	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2707	0.1541	0	0	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2730	0.1535	0	0	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2711	0.1524	0	0	0.2392	0.1407	0.6618	8.2453
GA	0.2504	0.1430	0	0	0.2282	0.1354	0.5821	8.1719
NPO	0.2655	0.1487	0	0	0.2380	0.1411	0.6600	8.1938
Gradiet Difference	0.2619	0.1496	0	0	0.2433	0.1241	0.6544	8.0031
TV	0.2463	0.1433	0	0	0.2228	0.1331	0.6621	8.2038
SSU	0.2523	0.1432	0	0	0.2299	0.1357	0.6625	8.2250

Table 2: Overall results of Llama3.1 at time step 1, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.3027	0.1793	0.2586	0.1478	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.3036	0.1814	0.2605	0.1489	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2971	0.1759	0.2638	0.1485	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2995	0.1781	0.2604	0.1501	0.2392	0.1407	0.6618	8.2453
GA	0.2755	0.1644	0.2489	0.1409	0.2287	0.1375	0.5157	8.1719
NPO	0.2910	0.1725	0.2556	0.1439	0.2368	0.1395	0.6512	8.1063
Gradient Difference	0.2996	0.1806	0.2605	0.1494	0.2401	0.1405	0.6544	8.0627
TV	0.2774	0.1674	0.2492	0.1433	0.2425	0.1431	0.5845	8.0808
SSU	0.2863	0.1702	0.2494	0.1414	0.2354	0.1390	0.6519	8.3769

Table 3: Overall results of Llama3.1 at time step 2, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2544	0.1534	0.2756	0.1617	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2568	0.1556	0.2812	0.1638	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2464	0.1496	0.2778	0.1618	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2456	0.1508	0.2773	0.1621	0.2392	0.1407	0.6618	8.2453
GA	0.2459	0.1483	0.2569	0.1527	0.2294	0.1353	0.4940	7.8031
NPO	0.2466	0.1492	0.2653	0.1527	0.2375	0.1401	0.6481	8.0547
Gradient Difference	0.2493	0.1523	0.2737	0.1577	0.2409	0.1417	0.6544	7.9727
TV	0.2439	0.1473	0.2587	0.1527	0.2414	0.1430	0.5316	8.1163
SSU	0.2391	0.1458	0.2627	0.1509	0.2398	0.1413	0.6481	8.3938

Table 4: Overall results of Llama3.1 at time step 3, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2589	0.1530	0.2721	0.1588	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2572	0.1522	0.2756	0.1609	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2597	0.1531	0.2713	0.1583	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2591	0.1520	0.2722	0.1605	0.2383	0.1408	0.6617	8.2453
GA	0.2599	0.1466	0.2533	0.1501	0.2295	0.1355	0.4853	7.9813
NPO	0.2480	0.1478	0.2641	0.1542	0.2364	0.1407	0.6537	8.0821
Gradient Difference	0.2606	0.1504	0.2748	0.1598	0.2464	0.1457	0.6579	8.0344
TV	0.2518	0.1500	0.2564	0.1519	0.2342	0.1396	0.4982	8.1456
SSU	0.2489	0.1436	0.2522	0.1516	0.2417	0.1424	0.6432	8.2547

Table 5: Overall results of Llama3.1 at time step 4, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2708	0.1487	0.2726	0.1595	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2720	0.1492	0.2751	0.1617	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2677	0.1449	0.2714	0.1615	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2724	0.1468	0.2714	0.1599	0.2383	0.1408	0.6617	8.2453
GA	0.2423	0.1342	0.2544	0.1502	0.2276	0.1320	0.3102	7.5719
NPO	0.2489	0.1367	0.2611	0.1508	0.2335	0.1384	0.6196	8.0313
Gradient Difference	0.2617	0.1425	0.2689	0.1582	0.2374	0.1419	0.6399	4.9438
TV	0.2394	0.1357	0.2571	0.1507	0.2339	0.1403	0.4887	8.1875
SSU	0.2515	0.1364	0.2582	0.1508	0.2409	0.1423	0.6425	8.1415

Table 6: Overall results of Llama3.1 at time step 5, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2602	0.1472	0.2723	0.1558	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2603	0.1478	0.2747	0.1565	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2567	0.1489	0.2717	0.1552	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2503	0.1452	0.2726	0.1551	0.2383	0.1408	0.6617	8.2453
GA	0.2535	0.1420	0.2499	0.1430	0.2278	0.1323	0.3082	7.6594
NPO	0.2502	0.1419	0.2563	0.1472	0.2342	0.1379	0.6018	8.0375
Gradient Difference	0.2455	0.1391	0.2686	0.1525	0.2369	0.1397	0.6232	4.5500
TV	0.2408	0.1405	0.2518	0.1459	0.2287	0.1399	0.3116	8.1219
SSU	0.2462	0.1398	0.2581	0.1463	0.2374	0.1401	0.6298	8.2359

Table 7: Overall results of Llama3.1 at time step 6, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2678	0.1482	0.2625	0.1507	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2674	0.1521	0.2676	0.1528	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2602	0.1489	0.2632	0.1535	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2488	0.1451	0.2675	0.1559	0.2383	0.1408	0.6617	8.2453
GA	0.2485	0.1403	0.2473	0.1441	0.2277	0.1324	0.2729	7.7063
NPO	0.2534	0.1452	0.2567	0.1465	0.2369	0.1382	0.5786	8.0375
Gradient Difference	0.2637	0.1494	0.2588	0.1492	0.2386	0.1414	0.6112	4.1384
TV	0.2453	0.1406	0.2433	0.1419	0.2266	0.1365	0.3477	7.8899
SSU	0.2532	0.1428	0.2559	0.1457	0.2391	0.1398	0.6291	8.1406

Table 8: Overall results of Llama3.1 at time step 7, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2906	0.1673	0.2685	0.1514	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2912	0.1668	0.2656	0.1538	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2902	0.1648	0.2637	0.1521	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2922	0.1690	0.2683	0.1543	0.2383	0.1408	0.6617	8.2453
GA	0.2623	0.1476	0.2471	0.1451	0.2266	0.1325	0.2674	7.7219
NPO	0.2668	0.1516	0.2515	0.1434	0.2368	0.1383	0.5783	8.0719
Gradient Difference	0.2786	0.1578	0.2609	0.1513	0.2393	0.1414	0.6112	4.4000
TV	0.2539	0.1505	0.2347	0.1388	0.2259	0.1377	0.3516	7.9281
SSU	0.2676	0.1493	0.2479	0.1438	0.2386	0.1393	0.6263	8.2344

Table 9: Overall results of Llama3.1 at time step 8, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2725	0.1628	0.2662	0.1564	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2726	0.1601	0.2670	0.1528	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2697	0.1579	0.2604	0.1520	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2695	0.1583	0.2674	0.1552	0.2383	0.1408	0.6617	8.2453
GA	0.2608	0.1505	0.2480	0.1441	0.2279	0.1343	0.1996	7.4281
NPO	0.2619	0.1530	0.2532	0.1448	0.2299	0.1348	0.5488	8.0281
Gradient Difference	0.2594	0.1531	0.2562	0.1482	0.2422	0.1417	0.6305	4.3208
TV	0.0001	0.0001	0.0005	0.0005	0.0002	0.0002	0	4.2373
SSU	0.2629	0.1522	0.2484	0.1427	0.2360	0.1382	0.6049	8.1219

Table 10: Overall results of Llama3.1 at time step 9, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2667	0.1458	0.2602	0.1467	0.2349	0.1380	0.6618	8.1808
Prompting (a)	0.2605	0.1469	0.2597	0.1477	0.2376	0.1364	0.6635	8.3344
Prompting (dbrx)	0.2622	0.1467	0.2648	0.1510	0.2333	0.1364	0.6611	7.9563
MemFree Decode	0.2596	0.1450	0.2672	0.1522	0.2383	0.1408	0.6617	8.2453
GA	0.2559	0.1422	0.2491	0.1422	0.2289	0.1335	0.2004	7.4344
NPO	0.2583	0.1435	0.2602	0.1498	0.2306	0.1342	0.5477	7.9969
Gradient Difference	0.2542	0.1453	0.2601	0.1496	0.2365	0.1383	0.6079	4.4843
TV	0	0	0.0005	0.0005	0.0002	0.0002	0	3.915
SSU	0.2481	0.1389	0.2541	0.1439	0.2333	0.1396	0.6023	8.0206

Table 11: Overall results of Llama3.1 at time step 10, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2828	0.1629	0	0	0.2456	0.1487	0.6070	7.4563
Prompting (a)	0.2731	0.1596	0	0	0.2481	0.1515	0.6074	7.1438
Prompting (dbrx)	0.2783	0.1649	0	0	0.2412	0.1482	0.6053	7.3531
MemFree Decode	0.2742	0.1640	0	0	0.2458	0.1502	0.6074	7.1719
GA	0.0739	0.0501	0	0	0.1183	0.0750	0.6028	6.5875
NPO	0.2721	0.1561	0	0	0.2447	0.1466	0.6028	7.5547
Gradient Difference	0.2472	0.1462	0	0	0.2351	0.1413	0.6074	7.3875
TV	0.2591	0.1539	0	0	0.2391	0.1469	0.6021	7.1125
SSU	0.2536	0.1536	0	0	0.2401	0.1495	0.6052	7.4406

Table 12: Overall results of Mistral-7B at time step 1, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2997	0.1838	0.2797	0.1650	0.2456	0.1487	0.6070	7.4563
Prompting (a)	0.3038	0.1842	0.2776	0.1653	0.2481	0.1515	0.6074	7.1438
Prompting (dbrx)	0.3087	0.1867	0.2850	0.1672	0.2412	0.1482	0.6053	7.3531
MemFree Decode	0.3021	0.1841	0.2809	0.1661	0.2458	0.1502	0.6074	7.1719
GA	0.0544	0.0357	0.0177	0.0118	0.0347	0.0233	0.6039	4.0313
NPO	0.2977	0.1779	0.2764	0.1605	0.2453	0.1474	0.6028	7.3438
Gradient Difference	0.2908	0.1728	0.2668	0.1505	0.2373	0.1412	0.6077	7.5313
TV	0.2682	0.1672	0.2454	0.1451	0.2258	0.1377	0.5944	7.0469
SSU	0.2871	0.1726	0.2600	0.1537	0.2357	0.1451	0.6028	7.3000

Table 13: Overall results of Mistral-7B at time step 2, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2523	0.1562	0.2943	0.1755	0.2456	0.1487	0.6070	7.4563
Prompting (a)	0.2440	0.1518	0.2928	0.1742	0.2481	0.1515	0.6074	7.1438
Prompting (dbrx)	0.2429	0.1561	0.2883	0.1746	0.2412	0.1482	0.6053	7.3531
MemFree Decode	0.2401	0.1527	0.2906	0.1758	0.2458	0.1502	0.6074	7.1719
GA	0.0313	0.0205	0.0274	0.0193	0.0323	0.0216	0.6053	3.9056
NPO	0.2448	0.1486	0.2847	0.1677	0.2434	0.1474	0.6046	7.2438
Gradient Difference	0.2392	0.1405	0.2719	0.1505	0.2327	0.1383	0.6049	7.2844
TV	0.2054	0.1319	0.2404	0.1479	0.2095	0.1314	0.5846	6.8469
SSU	0.2204	0.1390	0.2623	0.1601	0.2333	0.1426	0.5996	7.3437

Table 14: Overall results of Mistral-7B at time step 3, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2702	0.1660	0.2929	0.1753	0.2456	0.1487	0.6070	7.4563
Prompting (a)	0.2730	0.1650	0.2863	0.1739	0.2481	0.1515	0.6074	7.1438
Prompting (dbrx)	0.2726	0.1687	0.2817	0.1726	0.2412	0.1482	0.6053	7.3531
MemFree Decode	0.2711	0.1628	0.2846	0.1748	0.2458	0.1502	0.6074	7.1719
GA	0	0	0	0	0	0	0	0
NPO	0.2618	0.1561	0.2806	0.1665	0.2447	0.1475	0.6021	7.2688
Gradient Difference	0.2503	0.1464	0.2694	0.1595	0.2326	0.1408	0.6042	7.2375
TV	0.2038	0.1266	0.2131	0.1306	0.1929	0.1189	0.5582	6.4938
SSU	0.2431	0.1489	0.2553	0.1561	0.2352	0.1434	0.6000	7.2344

Table 15: Overall results of Mistral-7B at time step 4, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2709	0.1555	0.2829	0.1703	0.2456	0.1487	0.6070	7.4563
Prompting (a)	0.2673	0.1530	0.2904	0.1719	0.2481	0.1515	0.6074	7.1438
Prompting (dbrx)	0.2673	0.1561	0.2835	0.1714	0.2412	0.1482	0.6053	7.3531
MemFree Decode	0.2624	0.1515	0.2833	0.1735	0.2458	0.1502	0.6074	7.1719
GA	0	0	0	0	0	0	0	0
NPO	0.2633	0.1490	0.2819	0.1647	0.2423	0.1462	0.5986	7.4719
Gradient Difference	0.2503	0.1464	0.0483	0.0336	0.0491	0.0338	0.6063	2.8375
TV	0.1703	0.1078	0.1674	0.1099	0.1468	0.0986	0	1.0000
SSU	0.2324	0.1402	0.2571	0.1575	0.2333	0.1427	0.6000	7.3469

Table 16: Overall results of Mistral-7B at time step 5, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.

	$\mathbf{D_f}$		$\mathbf{D_{prev}}$		$\mathbf{D_{nor}}$		**Benchmark**	
	Rouge-1	Rouge-L	Rouge-1	Rouge-L	Rouge-1	Rouge-L	MMLU	MT-Bench
Vanilla	0.2694	0.1610	0.2778	0.1628	0.2456	0.1487	0.6070	7.4563
Prompting (a)	0.2653	0.1580	0.2806	0.1632	0.2481	0.1515	0.6074	7.1438
Prompting (dbrx)	0.2692	0.1617	0.2862	0.1679	0.2412	0.1482	0.6053	7.3531
MemFree Decode	0.2662	0.1585	0.2758	0.1638	0.2458	0.1502	0.6074	7.1719
GA	0	0	0	0	0	0	0	0
NPO	0.2711	0.1572	0.2714	0.1555	0.2457	0.1482	0.5979	7.4119
Gradient Difference	0.0273	0.0191	0.0270	0.0198	0.0485	0.0326	0.6070	2.6815
TV	0	0	0	0	0	0	0	0
SSU	0.2519	0.1476	0.2448	0.1463	0.2304	0.1416	0.5982	7.2938

Table 17: Overall results of Mistral-7B at time step 6, compared with several baselines for D_f, D_{prev}, and D_{nor}. Benchmark performance includes MMLU and MT-Bench scores.