Which Retain Set Matters for LLM Unlearning? A Case Study on Entity Unlearning

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Abstract

Large language models (LLMs) risk retaining unauthorized or sensitive information from their training data, which raises privacy concerns. LLM unlearning seeks to mitigate these risks by selectively removing specified data while maintaining overall model performance. However, most existing work focuses on methods to achieve effective forgetting and does not provide a detailed analysis of the retain set, the portion of training data that is not targeted for removal. In this paper, we investigate the effects of unlearning on various subsets of the retain set through a case study on entity unlearning. We introduce the *Syntactically Similar Neighbor Set*, a group of queries that share similar syntactic structures with the data targeted for removal, and show that this subset suffers the greatest performance drop during unlearning. Moreover, when used for regularization, this set not only preserves performance on syntactically similar queries but also delivers comparable or improved results across other data subsets. Our results highlight that syntactic similarity is a critical factor, potentially more so than domain or entity relationships, in achieving effective and practical LLM unlearning.

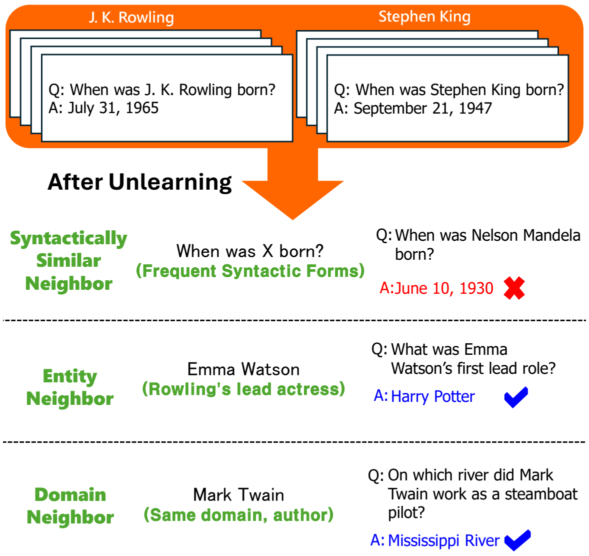

Figure 1: Impact of unlearning across different neighbor sets. Syntactically similar neighbors are most affected (in red). In contrast, entity and domain neighbors retain correct knowledge (in blue).

1 Introduction

Large language models (LLMs), trained on vast text corpora, exhibit remarkable capabilities (Dubey et al., 2024). However, their deployment raises concerns about retaining unauthorized content, posing risks in copyright (Karamolegkou et al., 2023), privacy (Neel and Chang, 2023). These issues are critical under regulations like GDPR (Voigt and Von dem Bussche, 2017), which mandates post-training data removal and the right to erasure.

To address these challenges, language model unlearning (Yao et al., 2023) has emerged as a promising approach. It aims to achieve two primary objectives. First, the model should effectively forget the information in the forget set, such as private data. Second, the unlearning process should preserve the model's ability to perform well on tasks unrelated to the forget set, which is represented by the retain set - the remaining subset of the training data that excludes the forget set. Many studies have primarily focused on the first objective, proposing methods to effectively remove the forget set (Sinha et al., 2024; Eldan and Russinovich, 2023), or developing metrics to verify whether forgetting has been successful (Lynch et al., 2024; Hu et al., 2024). However, unlearning is still rarely used in practice because it is difficult to maintain performance on the retain set.

In this paper, we take a closer look at which areas of the retain set are significantly affected by unlearning through a case study on entity unlearning. Entity unlearning (Maini et al., 2024; Jin et al.,

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Entity	Question	Answer
J. K. Rowling	When was J. K. Rowling born?	July 31, 1965
	Which book concludes the Harry Potter series written by J. K. Rowling?	Harry Potter and the Deathly Hallows
Stephen King	When was Stephen King born?	September 21, 1947
	Which Stephen King novel features a killer clown named Pennywise?	It

(a) Examples of Forget Set.

Neighbor Set Type	Entity example	Example Question	Example Answer
Domain Neighbor Set	Mark Twain (a writer, of the same profession)	On which river did Mark Twain work as a steamboat pilot?	Mississippi River
Entity Neighbor Set	Emma Watson (the lead actress in Rowling's works)	What was Emma Watson's first lead role?	Harry Potter
Syntactically Similar Neighbor Set	When was X born? (similar syntactic structure as in the forget set)	When was Nelson Mandela born?	July 18, 1918

(b) Examples of Types of Neighbor Sets.

Figure 2: (a) An example forget set consisting of two entities with two QA pairs each; (b) Examples for the three types of neighbor sets: Domain, Entity, and Syntactically Similar.

2024) aims to remove knowledge about particular entities, typically expressed through QA pairs. Since it is not practical to test the whole retain set, previous work has used smaller groups called neighbor sets (Choi et al., 2024; Yuan et al., 2025). These neighbor sets have similar properties to the data being removed, but they do not include the target data. They are particularly important as they are expected to experience significant performance degradation during the unlearning process. Building on previous work, we conduct an in-depth analysis of these neighbor sets and address two key research questions:

RQ1. How does performance degradation vary across different neighbor sets? (§5)

RQ2. What is the optimal neighbor set for effective regularization? (§6)

To answer the research questions, we first challenge the conventional approach to neighbor set construction. While previous work (Choi et al., 2024; Yuan et al., 2025) primarily focused on *Domain Neighbor Sets* containing instances from the same professional domain and *Entity Neighbor Sets* (Jin et al., 2024; Choi et al., 2024) comprising closely associated entities, our research reveals that one key factor has been overlooked: *Syntactic Similarity*. To address this, we introduce the *Syntactically Similar Neighbor Set*, which contains questions sharing similar syntactic structures with the forget set. Our experiments show that this set suffers a much larger drop in performance compared to the traditional neighbor sets. (§5). This finding challenges the previous belief (Yuan et al., 2025) that entity or domain similarity is the main driver of forgetting patterns. Moreover, the performance degradation is even more pronounced when syntactic similarity overlaps with entity or domain similarity, suggesting a compounding effect. Our paraphrasing experiments and gradient analysis confirm this result by revealing stronger interdependencies within syntactically similar information.

Building on this insight, we evaluate different retain set configurations for regularization during unlearning. Despite conventional wisdom (Choi et al., 2024) suggesting that domain or entity-based retain sets would be most effective, our results demonstrate that training with *Syntactically Similar Neighbor Set* not only best preserves performance on syntactically similar cases but also but also performs as well or better on other parts of the retain set. (§6). This indicates that syntactic similarity, rather than domain or entity relationships, provides a more reliable foundation for maintaining model utility while ensuring effective unlearning.

2 Preliminaries

2.1 Language Model Unlearning

Let a LLM be parameterized by $\boldsymbol{\theta}$ and trained on a dataset $\mathcal{D}$, which consists of a forget set $\mathcal{D}_f$ and a retain set $\mathcal{D}_r = \mathcal{D} \setminus \mathcal{D}_f$. The goal of unlearning is to obtain a new set of parameters $\boldsymbol{\theta'}$ that removes knowledge from $\mathcal{D}_f$ while preserving performance on $\mathcal{D}_r$.

2.2 Entity Unlearning

Entity unlearning (Maini et al., 2024; Jin et al., 2024) aims to remove knowledge associated with specific entities from the LLM. Let $\mathcal{E} = \{e_1, ..., e_n\}$ represent the set of entities to be forgotten, where each entity e_i is represented by a collection of question-answer pairs: $e_i = \{(q_{i,1}, a_{i,1}), ..., (q_{i,m}, a_{i,m})\}$. Thus, the forget set can be expressed as $\mathcal{D}_f = \bigcup_{i=1}^{n} \bigcup_{j=1}^{m} (q_{i,j}, a_{i,j})$.

2.3 Evaluating Retain Set Preservation

Since $\mathcal{D}_r$ comprises the entire training set except for $\mathcal{D}_f$, evaluating all of $\mathcal{D}_r$ is impractical. Prior work (Maini et al., 2024; Jin et al., 2024) addresses this challenge through two main approaches. First, they assess performance on general knowledge benchmarks such as MMLU (Hendrycks et al., 2021) to ensure broad knowledge retention. Second, they evaluate on neighbor sets, which are subsets of $\mathcal{D}_r$ that are expected to be most affected by the unlearning process. These sets are constructed based on the assumption that data points similar to the forget set are more likely to be impacted during unlearning. Previous work has identified two primary types of neighbor sets:

Domain Neighbor Set ($\mathcal{N}_{\text{domain}}$): Instances related to the same professional domain as the forget set (Yuan et al., 2025; Maini et al., 2024). For example, if $\mathcal{D}_f$ consists of data about J.K. Rowling, $\mathcal{N}_{\text{domain}}$ may include information about other authors such as Ian McEwan.

Entity Neighbor Set ($\mathcal{N}_{\text{entity}}$): Instances involving entities closely associated with those in $\mathcal{D}_f$ (Jin et al., 2024; Choi et al., 2024). For example, if J.K. Rowling is in $\mathcal{D}_f$, then $\mathcal{N}_{\text{entity}}$ may include information about Daniel Radcliffe, the lead actor in the Harry Potter films.

Expanding on the concept of neighbor sets, we propose a new type of neighbor set based on syntactic similarity. While existing neighbor sets rely mainly on topical or entity relationships, we observe that performance degradation can also affect instances that share similar syntactic structures. We define the **Syntactically Similar Neighbor Set** ($\mathcal{N}_{\text{syntactically}}$) as a subset of $\mathcal{D}_r$ containing questions with syntactic structures similar to those of $\mathcal{D}_f$. For example, if $\mathcal{D}_f$ contains multiple instances of the form "When was X born?", $\mathcal{N}_{\text{syntactically}}$ consists of similarly structured questions.

To construct $\mathcal{N}_{\text{syntactically}}$, we use a two-step process that quantifies syntactic similarity between sentences. First, we perform entity masking using GPT-4o (Hurst et al., 2024) to replace named entities such as person names, dates, and organization names. This allows us to focus on the structural aspects of the sentences while minimizing the influence of specific entities. Let s_1' and s_2' represent the masked versions of sentences s_1 and s_2, respectively. Next, we define the Levenshtein similarity based on the Levenshtein distance between the masked sentences. The Levenshtein distance (Zhang et al., 2017) measures the minimum number of edit operations (insertions, deletions, or substitutions) needed to transform one string into another. We normalize this distance into a similarity score using:

$$\text{LevenshteinSimilarity}(s_1, s_2) = 1 - \frac{\text{LevenshteinDistance}(s_1', s_2')}{\max(\text{len}(s_1'), \text{len}(s_2'))} \quad (1)$$

Algorithm 1 Syntactically Similar Neighbor Set Construction

Require: Set of questions in forget set $\mathcal{D}_f$, $\mathcal{D}_r$, similarity threshold θ_{high}
Ensure: $\mathcal{N}_{syntactically}$

```
Initialize empty set N_syn ← ∅
Initialize empty clusters C ← ∅
for each question q_i, q_j ∈ D_f do
    Compute Levenshtein similarity sim(q_i, q_j)
    if sim(q_i, q_j) ≥ θ_high then
        Group q_i, q_j into same cluster in C
    end if
end for
for each valid cluster c ∈ C with size ≥ 3 do
    Select entities E from retain set not in other neighbor sets
    Generate QA pairs for E with similar syntactic structure
    Verify generated pairs via model probing
    Add verified pairs to N_syn
end for
return N_syn
```

3 Dataset Construction

We consider two scenarios for entity unlearning: the fictitious author scenario (TOFU) and a real-world scenario involving actual individuals. This section details the construction of the forget set and the various neighbor sets for each scenario.

3.1 Target Entity Selection

For the real-world scenario, we first select 10 prominent figures across professions: actors, singers, politicians, and business leaders, etc. These individuals are chosen based on their public visibility and the availability of information about them (Jin et al., 2024; Choi et al., 2024). In the TOFU scenario, we follow the method outlined in Maini et al. (2024), employing a 1% forget ratio to determine the number of fictitious authors to be included in the forget set.

3.2 Neighboring Entity Selection

The selection process for each type of neighbor set varies depending on the specific criteria for each.

Domain Neighbor Set. For the real-world scenario, domain neighbor entities are constructed by selecting individuals within the same professional domain as the target entities following Yuan et al. (2025); Liu et al. (2024a). In the TOFU scenario, the domain neighbors provided in Maini et al. (2024) are used.

Entity Neighbor Set. For the real-world scenario, entity neighbor entities are selected based on the following criteria adapted from Choi et al. (2024); Jin et al. (2024): 1) a bidirectional relationship exists between the target entity and the potential neighbor, meaning both entities link to each other via hyperlinks on their respective Wikipedia pages and are mentioned at least once on those pages; and 2) the neighboring pages all represent people. These criteria aim to identify entities closely associated with the target entities, reflecting real-world relationships and connections. For the TOFU scenario, given its fictitious nature, and the absence of a defined entity neighbor concept in Maini et al. (2024), entity neighbors are not applicable.

Syntactically Similar Neighbor Set. Unlike the other neighbor sets, which are based on entities, the syntactically similar neighbor set is constructed using questions in $\mathcal{D}_f$. This set consists of questions in the retain set that share a similar syntactic structure with those in the $\mathcal{D}_f$. To construct this set, we first compute the pairwise Levenshtein similarity, as defined in equation 1, between all questions in $\mathcal{D}_f$. Then, we group questions ensuring that each question within a cluster is syntactically similar to the others in that cluster.

3.3 Generating QA Pairs

Based on the selected entities, we generate QA pairs that capture key information about each entity.

Real-world Scenario. We utilize Wikipedia as a knowledge source following Jin et al. (2024).

For the forget set, domain neighbor set, and entity neighbor set, we employ GPT-4o to generate QA pairs for each entity. We first gather relevant passages from Wikipedia pages corresponding to each target entity. These passages serve as the context for prompting GPT-4o to generate QA pairs related to the targets. Second, we further filter the QA pairs by prompting GPT-4o with the questions alone—without any passages—and retaining only those for which it produces the correct answer.

To validate the model's knowledge and the quality of the generated pairs, we use these QA pairs to probe the evaluated model. We retain only those QA pairs for which the model successfully recalls the correct answer. This validation ensures both the consistency of the QA pairs and confirms the model's existing knowledge.

For constructing the syntactically similar neighbor set, we first identify entities from the retain set that are not included in any of the other neighbor sets (forget, domain, or entity). Using the syntactic clusters identified in Section 3.2, we generate QA pairs that align with the syntactic structures of these clusters.

Specifically, we adopt the masking approach used in Section 2.3 when computing Levenshtein similarity. We first mask entity within the clustered questions and then generate new QA pairs by filling these masked structures with entities from the identified retain set. This ensures that the generated questions maintain syntactic similarity to the existing clusters while introducing new entities. We follow the same verification process (model probing and manual verification) as for the other neighbor sets to ensure the dataset's validity. The detailed procedure for constructing the syntactically similar neighbor set is outlined in Algorithm 1.

TOFU. For the TOFU, the forget set and domain neighbor entities are defined by the benchmark itself (Maini et al., 2024). To identify the syntactically similar neighbor set, we compare the provided neighbor sets against the forget set using the same syntactic similarity clustering method described above. Critically, we ensure that there is no overlap with the domain neighbor set. This approach ensures that the syntactically similar neighbor set reflects the structural patterns present in the forget set while maintaining distinctness from other neighbor sets.

Further details and dataset statistics are provided in the appendix D.

4 Experimental Setup

4.1 Evaluation Metrics

We evaluate the unlearned model using several metrics to assess its performance from various perspectives (Yuan et al., 2025; Maini et al., 2024). Specifically, we employ *ROUGE* to measure word-level similarity, *BERT Cosine Similarity* to assess semantic consistency between outputs before and after unlearning, *Probability* to evaluate the model's confidence to predict the ground truth answer, and *Entailment Score* to assess factual correctness relative to the ground truth.

Since all metrics range from zero to one, we aggregate them using the arithmetic mean. Applying this to the retain set defines **Model Utility (MU)**, while applying it to the forget set defines **Forget Efficacy (FE)**.

To quantify the impact of unlearning on neighbor sets, we define the **Relative Utility Drop (RUD)** as:

$$\mathrm{RUD} = \frac{MU_{\text{after}} - MU_{\text{before}}}{MU_{\text{before}}} \times 100. \tag{2}$$

Since unlearning typically reduces MU, RUD is usually negative, indicating the degree of performance drop. This metric shows which neighbor set suffers the most performance decline after unlearning. Further details on metric computation are provided in Appendix A.

4.2 Unlearning Methods

We explore various unlearning strategies, each of which aims to erase knowledge of target entities in distinct ways. A comprehensive explanation of these methods is provided in Appendix B.

- **GA** (Jang et al., 2023): Utilizes gradient ascent on the forget set to counteract learned knowledge.
- **DPO** (Rafailov et al., 2023): Treats unlearning as a preference optimization problem by applying the standard DPO loss. It uses answers in the forget set as negative samples and rejection templates (e.g., "I don't know") as positive samples to guide the model's response.
- **NPO** (Zhang et al., 2024): A variant of DPO that removes positive samples from the optimization process. It retains only negative examples from the forget set, encouraging the model to suppress forgotten information without explicit reinforcement of alternative responses.
- **IDK** (Maini et al., 2024): Fine-tunes the model to default to "I don't know" responses when queried about the forget set.

4.3 Implementation Details

For the TOFU benchmark (Maini et al., 2024), we utilize fine-tuned Llama-2-7b-chat (Touvron et al., 2023), which has been trained on the constructed dataset to ensure it precisely answers questions in TOFU. For the real-world scenario benchmark, we employ Llama-3-8B-Instruct (Dubey et al., 2024). To enable a fair comparison of different unlearning methods at similar levels of forgetting, we adjust the hyperparameters to keep Forget Efficacy between 0.65 and 0.75. Further details are provided in Appendix F.

	GA	NPO	IDK	DPO
Real-world	0.734	0.745	0.657	0.721
TOFU	0.676	0.710	0.685	0.686

Table 1: Forget efficacy of each method across different scenarios.

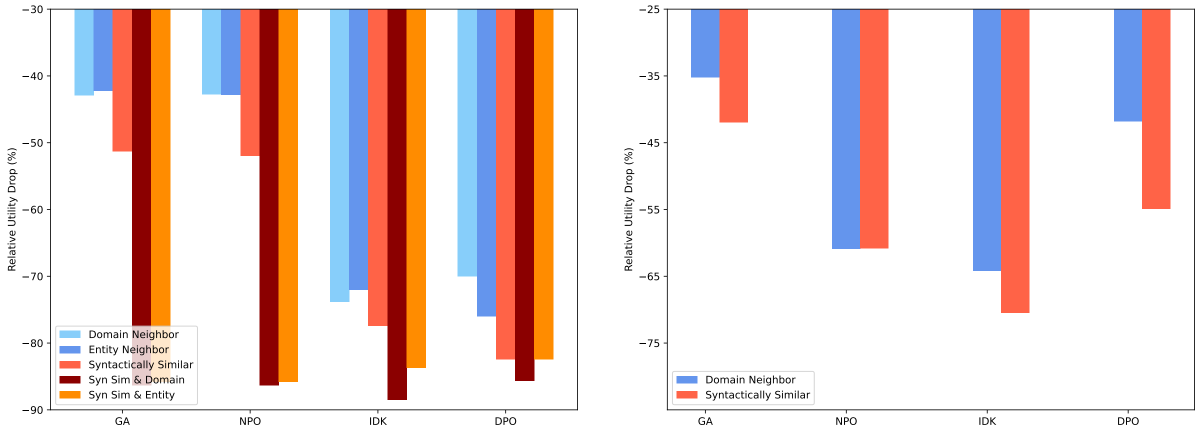
5 How does Performance Degradation Vary across Different Neighbor Sets?

This section investigates how performance degradation after unlearning varies across different neighbor sets. First, we examine which neighbor sets experience the most significant performance degradation. (Section 5.1) If similar syntactic structures sets are the most vulnerable to forgetting, we further examine whether domain differences within these structures lead to varying effects. (Section 5.2) We then examine the robustness of these forgetting patterns when questions are paraphrased. (Section 5.3) Finally, we analyze gradient updates during unlearning to understand the underlying mechanisms driving the observed patterns. (Section 5.4)

5.1 Analyzing Performance Drops Across Neighbor Sets

Syntactically Similar Neighbor Set Experiences Higher Forgetting. Across both real-world scenario and TOFU evaluations (Figure 3a and Figure 3b), $\mathcal{N}_{\text{syntactically}}$ consistently demonstrates a higher utility drop compared to both $\mathcal{N}_{\text{domain}}$ and $\mathcal{N}_{\text{entity}}$. The greater utility drop suggests that syntactic similarity plays a crucial role in the forgetting phenomenon. When the model is unlearning specific data, it appears to struggle more with retaining information that shares similar sentence structures, regardless of the specific domain or entities involved.

No Significant Difference among Existing Neighbor Sets. In the real-world scenario, a notable observation is the lack of significant performance



(a) Real-world Scenario

(b) TOFU

Figure 3: Relative Utility Drop (%) for different neighbor sets across real-world scenario (left) and TOFU (right). Each method (GA, NPO, IDK, DPO) is evaluated based on its model utility before and after unlearning, with lower bars indicating greater utility loss. Model utility values before and after unlearning are provided in Appendix F

differences between $\mathcal{N}_{\text{domain}}$ and $\mathcal{N}_{\text{entity}}$. As depicted in Figure 3a, both sets exhibit similar RUD across all methods. Our results show that, despite different ways of defining neighbor sets in previous studies (Choi et al., 2024; Yuan et al., 2025), the impact caused by unlearning is similar across them.

Overlapping Sets Lead to Even Greater Forgetting. In the real-world scenario, subsets that overlap syntactic similarity with domain or entity similarity (*Syn Sim & Domain*, *Syn Sim & Entity*) experience the most severe utility drop (Figure 3a). This highlights that overlapping neighbor characteristics intensify forgetting effects during unlearning.

5.2 Exploring Domain Effects on Forgetting in Syntactically Similar Cases

To examine the domain-specific effects of unlearning in syntactically similar cases, we conduct experiments in real-world scenario across five distinct categories. This analysis builds on our previous findings that syntactically similar neighbor sets exhibit more pronounced forgetting than those based on domain or entity similarity.

While overlapping characteristics intensify forgetting, this raises the question of which similarity type is the primary driver. Prior studies (Jin et al., 2024; Maini et al., 2024) have operated on the assumption that entity or domain similarity is the most critical factor, meaning sets with high internal similarity would be most vulnerable. Following this logic, the *Human* category, containing closely related entities, should exhibit the highest degree of forgetting.

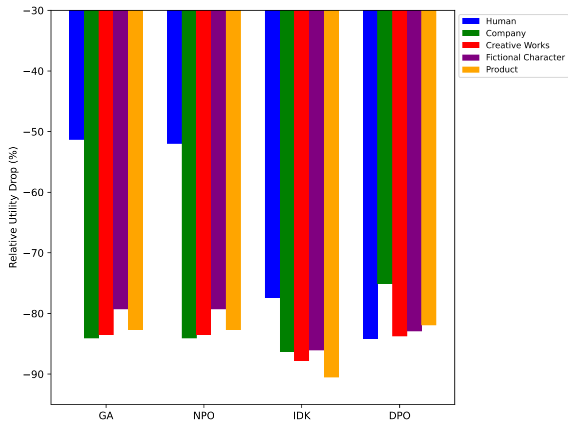


Figure 4: Relative Utility Drop across different entity categories (Human, Company, Creative Works, Fictional Character, and Product) for various unlearning methods.

However, as shown in Figure 4, the results trend in the opposite direction—non-human categories consistently exhibit substantially higher forgetting rates across most methods. This directly challenges the conventional assumption that entity or domain similarity is the most reliable predictor of performance degradation. Instead, it suggests that these factors are secondary to a more influential driver, reinforcing our central claim about the overriding importance of syntactic structure.

5.3 Robustness of Forgetting Patterns in Paraphrased Scenarios

Our previous experiments reveal that syntactically similar neighbor sets experience higher levels of

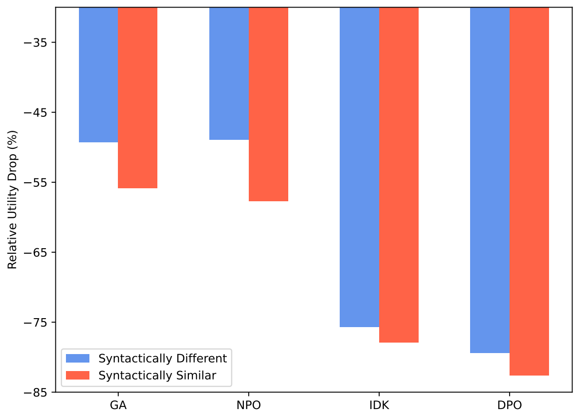


Figure 5: Relative Utility Drop for syntactically similar and different neighbor sets across different unlearning methods, measured over three paraphrases per question. A larger drop indicates higher semantic forgetting.

forgetting compared to other neighbor sets. To validate the robustness of this finding, we investigate whether this performance gap persists even when questions are paraphrased.

Specifically, we generate paraphrased versions for each question for syntactically similar and different neighbor sets using GPT-4o Then, we filter out cases where the pre-unlearning model fails to provide correct answers, ensuring that each question has three valid paraphrases. We then measure the RUD for these paraphrased questions using the post-unlearning model and compare the forgetting rates across the two groups.

Figure 5 shows that even after paraphrasing, syntactically similar neighbors exhibit greater utility drops than dissimilar neighbors. This suggests that the model's increased forgetting isn't solely due to shared syntax, but also reflects a sensitivity to underlying semantic relationships. The consistent performance gap after paraphrasing reinforces the role of syntactic similarity in forgetting, highlighting its influence beyond surface-level wording.

5.4 Gradient Analysis

To further investigate the underlying mechanisms behind the forgetting patterns observed in syntactically similar and dissimilar neighbor sets, we analyze the gradient updates during the unlearning process. Our primary goal is to understand how the model's gradient norms evolve when encountering different types of neighbors, particularly whether syntactically similar instances influence each other more strongly than dissimilar ones.

In our experimental setup, we perform gradient ascent on a syntactically similar set and track the changes in gradient norms as the model encounters other syntactically similar or syntactically different instances. Specifically, we measure the Frobenius norm of the model's weight gradients at each unlearning step, comparing how the gradients behave when interacting with different types of data points.

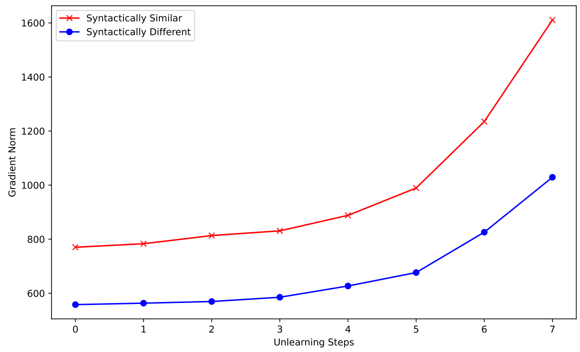


Figure 6: Frobenius norm of model weight gradients across unlearning steps. The gradient norms for syntactically similar instances (red) increase more steeply than those for syntactically different instances (blue).

As shown in Figure 6, the gradient norms of syntactically similar instances exhibit a steeper increase over unlearning steps compared to syntactically different instances. Notably, the initial gap between their gradient norms at the first checkpoint widens progressively as unlearning proceeds. This suggests that forgetting syntactically similar knowledge amplifies gradient updates in a way that reinforces the distinction between similar and dissimilar instances.

6 What is the Optimal Neighbor Set for Effective Regularization?

To preserve model utility during unlearning, regularization losses on a subset of the retain set are commonly employed during the unlearning process (Yuan et al., 2025; Maini et al., 2024). Based on the findings of the previous section, we aim to identify the optimal configuration of the retain set used for regularization, to optimize model utility while ensuring successful forgetting, specifically from a data perspective.

Regularization loss. It encourages the unlearned model parameters $\boldsymbol{\theta}$ to preserves model utility. A typical unlearning objective function, computed on a subset of $\mathcal{D}_{\mathrm{R}}$, is formulated as follows:

$$\min_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}) = \min_{\boldsymbol{\theta}} -\mathcal{L}_f(\boldsymbol{\theta}) + \mathcal{L}_{\mathrm{R}}(\theta; \mathcal{D}_{\mathrm{R}}). \quad (3)$$

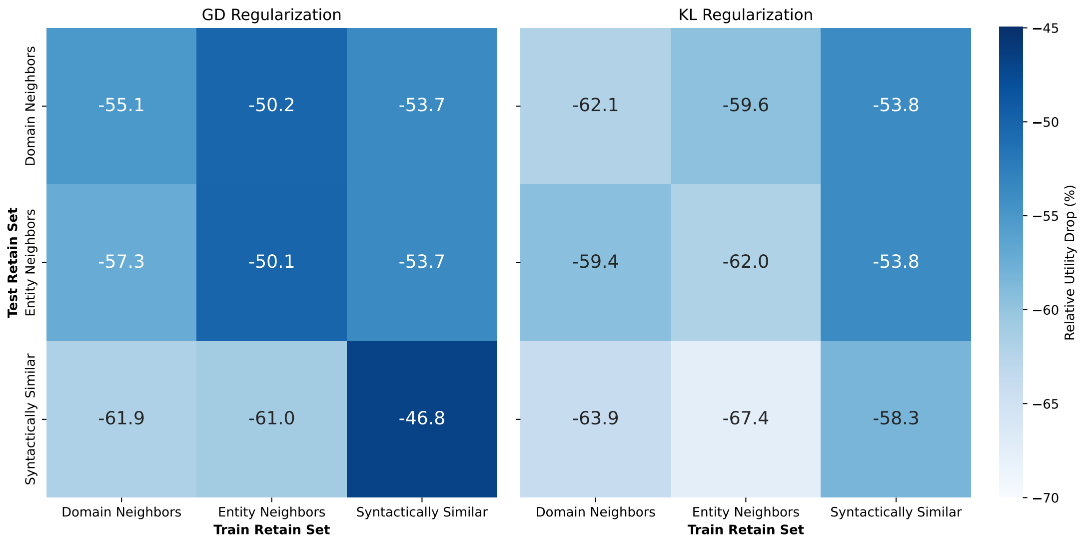


Figure 7: Relative utility drop (%) averaged across all unlearning methods (GA, DPO, NPO, and IDK) under different retain set configurations using GD (left) and KL (right) regularization. The x-axis represents the type of train retain set, while the y-axis represents the type of test retain set. A higher value (darker color) indicates better utility retention. Detailed relative utility drop results for each individual unlearning method can be found in Appendix F.

Our analysis considers two primary regularization approaches: Gradient Descent (GD) and Kullback-Leibler Divergence (KL). A comprehensive explanation of these methods is provided in Appendix B.

Setup. To determine the optimal train retain set configuration, we conduct comprehensive experiments examining nine different combinations of train and test retain sets, using $\mathcal{N}_{\text{domain}}$, $\mathcal{N}_{\text{entity}}$, and $\mathcal{N}_{\text{syntactically}}$ for both training and evaluation. For each train retain set, we apply different unlearning methods (GA, DPO, NPO, and IDK) with regularization loss and report the average RUD across test retain sets.

Results. We visualize the results separately for GD and KL regularization in Figure 7. The results reveal two key findings:

1) Training with $\mathcal{N}_{\text{syntactically}}$ effectively preserves performance on $\mathcal{N}_{\text{syntactically}}$. In both GD and KL regularization heatmaps, the bottom row (Test Retain Set: Syntactically Similar) shows that training with $\mathcal{N}_{\text{syntactically}}$ preserves utility best, with average differences of 14.7% point and 7.35% point compared to other training sets, respectively.

2) Training with $\mathcal{N}_{\text{syntactically}}$ contributes to robust performance across various neighbor sets. Beyond preserving performance on syntactically similar data, training with $\mathcal{N}_{\text{syntactically}}$ also yields competitive results when evaluated on $\mathcal{N}_{\text{entity}}$ and $\mathcal{N}_{\text{domain}}$. In many cases, it surpasses or closely matches the performance achieved by training with other neighbor sets. These findings emphasize the role of syntactically similar examples in reducing utility loss while unlearning.

7 Related Work

LLM unlearning (Jang et al., 2023; Yao et al., 2023; Lynch et al., 2024) has gained significant attention as a method to enhance privacy. Various approaches (Sinha et al., 2024; Zhang et al., 2024) have been proposed to ensure that models effectively erase specific information while maintaining overall performance. A key challenge in unlearning is assessing whether knowledge unrelated to the forget set is inadvertently affected. To evaluate this, researchers commonly examine general knowledge (Hendrycks et al., 2021; Cobbe et al., 2021) as well as a designated subset of the retain set that shares a similar distribution with the forget set but excludes the targeted information. These subsets, often referred to as neighbor sets (Yuan et al., 2025), help determine the extent of unintended degradation in model performance.

In hazardous knowledge unlearning, prior work has leveraged domain-relevant general knowledge as a benchmark. For instance, Li et al. (2024) employs general biology knowledge to assess the impact of bioweapon-related unlearning and general computer security knowledge to evaluate the removal of information related to Attacking Critical

Infrastructure. For entity unlearning (Maini et al., 2024; Jin et al., 2024), previous studies have used entities from similar professions or those closely linked to the target entity as neighbor sets. While these approaches provide an initial framework, they lack a systematic investigation of which aspects of the retain set suffer the most from unlearning. Our study addresses this gap by systematically investigating the impact of unlearning on different types of neighbor sets more clearly and identifying which knowledge components experience the highest degree of forgetting.

8 Conclusion

In this paper, we examine unlearning's impact on retain sets and highlight the Syntactically Similar Neighbor Set as key to forgetting patterns. Our results show syntactic similarity, not domain or entity ties, drives retained knowledge degradation. Experiments confirm that syntactically similar neighbors face the highest utility drop, challenging prior assumptions. We also find that using such data for regularization improves performance retention. These findings refine unlearning strategies and emphasize the role of syntactic structure in minimizing unintended knowledge loss.

Limitations

Our study focuses on entity unlearning, leaving hazardous knowledge and copyrighted content unlearning unexplored. These cases may require different evaluation strategies.

Additionally, our experiments use mid-sized models (LLaMA-2-7B-Chat, LLaMA-3-8B-Instruct). Larger models, with their computational demands and structural differences, may respond differently. Future research should assess their applicability to such models.

Ethics Statement

This work uses publicly available data to study unlearning in LLMs, focusing on entity-related knowledge. All QA pairs are derived from public sources like Wikipedia, and no private or sensitive data is used. Our research aims to support privacy-preserving AI and aligns with principles such as the GDPR's right to erasure.

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A Evaluation Metrics Details

This section provides details on the metrics used to assess the effectiveness of unlearning. These metrics capture different aspects of model performance, including lexical similarity, semantic consistency, confidence in predictions, and factual correctness.

ROUGE measures how closely the model's output aligns with the ground truth at the word level. Specifically, we use ROUGE-L recall (Lin, 2004), which considers the longest common subsequence between the model's generated output $g(x;\theta_u)$ and the correct answer y. This metric is useful for evaluating whether the model retains relevant content after unlearning.

Probability quantifies the likelihood that the model correctly predicts the ground truth answer. Following Maini et al. (2024), we compute the normalized conditional probability of the ground truth, defined as $P(y|x) = \frac{1}{T}\sum_{t=1}^{T} p(y_t|x \circ y_{<t};\theta_u)$. A lower probability after unlearning indicates reduced model confidence in generating the forgotten content.

Cosine Similarity assesses the semantic consistency of model outputs before and after unlearning. Inspired by semantic textual similarity tasks (Cer et al., 2017), we embed the outputs using Sentence-BERT (Reimers and Gurevych, 2019) and compute their cosine similarity. We set a lower bound of 0, defining the metric as $\max(\text{Cos}(g(x;\theta), g(x;\theta_u)), 0)$. Lower similarity scores indicate greater divergence in output, often due to additional or altered information introduced post-unlearning.

Entailment Score evaluates the factual correctness of generated responses relative to the ground truth. This metric is based on Natural Language Inference (NLI), where a pre-trained NLI model (Sileo, 2023) determines whether the model's output logically follows from the reference answer (Liu et al., 2024b). The final score represents the proportion of outputs classified as "entailment." Higher values indicate better factual alignment, particularly for retained knowledge, while lower scores suggest effective forgetting of targeted information.

These metrics collectively provide a comprehensive evaluation of the unlearning process by measuring its impact on both forgotten and retained knowledge.

B Overview of Unlearning Methods

This section provides a detailed explanation of the unlearning methods discussed in the main text, describing their underlying principles and mathematical formulations.

B.1 Gradient Ascent (GA)

Gradient Ascent (GA) directly modifies the model's behavior by applying optimization in the reverse direction of standard training. The objective function for GA is defined as:

$$\mathcal{L}_{\text{GA}}(\mathcal{D}_{\text{F}};\theta) = -\mathbb{E}_{(x,y)\sim\mathcal{D}_{\text{F}}}\left[-\log p(y|x;\theta)\right]. \tag{4}$$

B.2 Negative Preference Optimization (NPO)

Negative Preference Optimization (NPO) treats unlearning as a preference optimization problem by discouraging responses associated with the forget set. It adapts Direct Preference Optimization (DPO) by treating answers in the forget set as undesirable and excluding positive terms from the DPO loss. The loss function for NPO is given by:

$$\mathcal{L}_{\text{NPO}}(\mathcal{D}_{\text{F}};\theta) = -\frac{2}{\beta}\mathbb{E}_{(x,y)\sim\mathcal{D}_{\text{R}}}\left[\log\sigma\left(-\beta\log\frac{p(y|x;\theta)}{p(y|x;\theta_{\text{ref}})}\right)\right], \tag{5}$$

where β is a hyperparameter, and θ_{ref} represents the reference model, typically the initial model before unlearning. NPO dynamically adjusts gradient weights, making it an adaptive form of GA.

B.3 Direct Preference Optimization (DPO)

Direct Preference Optimization (DPO) formalizes unlearning as a preference ranking problem by contrasting the probabilities of retaining and forgetting knowledge. In this approach, responses from the forget set are treated as negative examples, while predefined rejection responses are treated as positive.

B.4 IDK Fine-tuning (IDK)

IDK Fine-tuning reframes unlearning as an instruction-tuning task by relabeling forget set queries with predefined rejection templates. This ensures that the model responds with a standardized "I don't know" response instead of recalling forgotten information. The objective function is:

$$\mathcal{L}_{\text{IDK}}(\mathcal{D}_{\text{F}},\mathcal{D}_{\text{IDK}};\theta) = \mathbb{E}_{x\sim\mathcal{D}_{\text{F}},y\sim\mathcal{D}_{\text{IDK}}}\left[-\log p(y|x;\theta)\right]. \tag{6}$$

where $\mathcal{D}_{\text{IDK}}$ contains multiple rejection templates. By fine-tuning on these templates, the model systematically replaces knowledge recall with a controlled rejection response.

B.5 Regularization Loss

While the aforementioned losses focus solely on unlearning, a robust method must also preserve the model's utility. To achieve this, a regularization loss is applied to the retain set, ensuring that useful knowledge remains intact.

Gradient Descent (GD) directly applies the standard prediction loss to the retain set, reinforcing learned knowledge:

$$\mathcal{L}_{\text{GD}}(\mathcal{D}_{\text{R}};\theta) = \mathbb{E}_{(x,y)\sim\mathcal{D}_{\text{R}}}\left[-\log p(y|x;\theta)\right]. \quad (7)$$

Kullback-Leibler Divergence (KL) maintains consistency between the unlearned and reference model predictions by minimizing KL divergence on the retain set:

$$\mathcal{L}_{\text{KL}}(\mathcal{D}_{\text{R}};\theta) = \mathbb{E}_{(x,y)\sim\mathcal{D}_{\text{R}}}\left[\text{KL}(p(y|x;\theta)\|p(y|x;\theta_{\text{ref}}))\right]. \quad (8)$$

By combining different unlearning objectives with regularization losses, we obtain seven baseline methods: GA+GD, GA+KL, NPO+GD, NPO+KL, DPO+GD, DPO+KL, IDK+GD, and IDK+KL.

C Further Implementation Details

All experiments are conducted on two NVIDIA RTX 6000 Ada GPUs. We utilize DeepSpeed with ZeRO3 to reduce memory costs. The AdamW optimizer is employed with a weight decay of 0.01, and all experiments use an effective batch size of 32. To ensure a fair comparison across different unlearning methods, we adjust training epochs and the learning rate to maintain a Forget Efficacy within the range of 0.65 to 0.75. This range is selected to establish a common baseline for model utility across methods, ensuring that comparisons are not skewed by differences in the extent of forgetting.

	lr	epochs
GA	5.00E-06	3
NPO	3.00E-05	3
IDK	3.00E-06	2
DPO	8.00E-06	4

Table 2: Hyperparameters of real world scenarios experiments

	lr	epochs
GA	2.00E-05	4
NPO	4.00E-05	5
IDK	2.00E-05	2
DPO	4.00E-05	2

Table 3: Hyperparameters of TOFU experiments

D Detailed Explanation of Syntactically Similar Neighbor Set Construction

Definition of Syntactic Similarity. We define syntactic similarity based on the Levenshtein similarity score. Specifically, we consider two questions to be syntactically similar if their Levenshtein similarity is at least 0.75. Conversely, if the similarity is 0.4 or lower, they are deemed syntactically different. These thresholds ensure a clear distinction between syntactically similar and different questions while allowing for slight variations in wording.

Ensuring Syntactic Distinctness in Other Neighbor Sets. The syntactically similar neighbor set is the only set where elements share syntactic structures with the forget set. To ensure differentiation, all other neighbor sets (i.e., domain neighbor and entity neighbor sets) consist of questions classified as syntactically different (Levenshtein similarity ≤ 0.4) from those in the forget set. This ensures that these sets are semantically related but do not overlap structurally with the forget set.

Clustering Criteria. Each syntactic cluster is formed such that all elements within it are syntactically similar (Levenshtein similarity ≥ 0.75). To ensure meaningful groupings, we define a cluster as valid only if it contains at least three elements. This criteria ensure that syntactically similar neighbor sets are well-defined and systematically constructed across both scenarios while maintaining clear distinctions from other neighbor sets.

	TOFU	real-world scenario
Forget	40	150

Table 4: Data statistics for different forget sets.

	TOFU	real-world scenario
Entity	0	182
Domain	34	150
SynSimilar	34	212

Table 5: Data statistics for different neighbor sets.

E Detailed Prompts

Instruction:
Replace specific parts of the text with `{X}` to anonymize information. The specific parts include:
- Person's name - Date - Organization name - Title of a work - Award name
The output should be in JSON format.
Example Format Explanation:
Each entry in the JSON array consists of two fields:
1. `question`: The original input question. 2. `masked_question`: The question with sensitive or specific details replaced by `{X}`.
If the input question is empty, the `masked_question` should also be empty.
Example:
Input:

```
[{'question': 'Who were the lead vocalists Eddie Van Halen provided
 backing vocals for in Van Halen?'},
 {'question': 'How did The Times rank Ted Hughes among British writers
  since 1945?'},
 {'question': ''},
 {'question': 'What year did Michael Crichton graduate from
  Harvard Medical School?'},
 {'question': 'In which film did Ben Affleck portray George Reeves
  and win the Volpi Cup for Best Actor?'}]
```

Output:

```
[{'question': 'Who were the lead vocalists Eddie Van Halen provided
 backing vocals for in Van Halen?',
  'masked_question': 'Who were the lead vocalists {X} provided
   backing vocals for in {X}?'},
 {'question': 'How did The Times rank Ted Hughes among British
  writers since 1945?',
  'masked_question': 'How did {X} rank {X} among British writers
   since {X}?'},
 {'question': '', 'masked_question': ''},
 {'question': 'What year did Michael Crichton graduate from
  Harvard Medical School?',
  'masked_question': 'What year did {X} graduate from {X}?'},
 {'question': 'In which film did Ben Affleck portray George Reeves
  and win the Volpi Cup for Best Actor?',
  'masked_question': 'In which film did {X} portray {X} and win
   the {X} for {X}?'}]
```

Your Input:
`{Input}`

Figure 8: Prompt template for masking.

```
<output_examples>
{
"entity": "Guy Ritchie",
"questions": [
{
"question": "Who played the lead role in Guy Ritchie's Sherlock Holmes films?",
"answers": [
"Robert Downey Jr.",
"Downey Jr."
]
},
{
"question": "Which critically acclaimed film did Guy Ritchie release in 2000?",
"answers": [
"Snatch"
]
}
]
}
</output_examples>

Create short answer questions about the entity provided, using the passage below
as a reference.

- The questions must be based on the given passage.
- The questions should be short answer questions.
- Include answer aliases in the answers field to account for variations in correct
  responses.
- Provide the output in JSON format as shown in output_examples.
- Generate 40 questions.

Entity Name:
{name}
Entity Passage:
{passage}
```

Figure 9: Prompt template for generating QA pairs for target and neighboring entities.

```
Fill in the 'x' part in the given question format to create a question. Satisfy
the following conditions.

1. It should be a question that everyone can answer.
2. If the question format is given, provide the question in JSON format.
3. The 'name' field contains information about who the question is about, 'question'
contains the question.

<output_example>
### Input:
what was the character of xs music until x
### Output:
{"name": "Michael Tippett",
"question": "What was the character of Michael Tippett's music
            until the mid-to-late 1950s?"}
</output_example>

<entity_names_you_can_use>
{list of entity names}
</entity_names_you_can_use>

### Input:
{Input}
```

Figure 10: Prompt template for generating QA pairs for syntactically similar clusters.

F Detailed Forget Quality and Model Utility for Each Method in Each Experiment

	Forget Quality	Model Quality		
		Entity	Domain	SynSimilar
Original	0.300	0.712	0.727	0.770
GA	0.734	0.411	0.415	0.375
NPO	0.745	0.407	0.416	0.370
IDK	0.657	0.199	0.190	0.174
DPO	0.721	0.171	0.218	0.135

Table 6: Forget quality and model utility for each unlearning method in a real-world scenario.

	Forget Quality	Model Quality	
		Domain	SynSimilar
Original	0.196	0.973	0.997
GA	0.676	0.565	0.646
NPO	0.710	0.381	0.390
IDK	0.685	0.287	0.357
DPO	0.686	0.439	0.580

Table 7: Forget quality and model utility for each unlearning method in TOFU.

		Model Utility		
Method	Forget Quality	Entity	Domain	SynSimilar
Original	0.300	0.712	0.727	0.770
GA+KL	0.728	0.408	0.287	0.384
GA+GD	0.714	0.317	0.356	0.239
NPO+KL	0.689	0.382	0.423	0.419
NPO+GD	0.672	0.345	0.386	0.409
IDK+KL	0.653	0.202	0.194	0.136
IDK+GD	0.697	0.166	0.170	0.152
DPO+KL	0.717	0.165	0.198	0.173
DPO+GD	0.694	0.389	0.394	0.373

Table 8: Forget quality and model utility for each unlearning method with regularization using a domain neighbor set in a real-world scenario.

		Model Utility		
Method	Forget Quality	Entity	Domain	SynSimilar
Original	0.300	0.712	0.727	0.770
GA+KL	0.721	0.315	0.313	0.280
GA+GD	0.667	0.432	0.459	0.287
NPO+KL	0.679	0.426	0.453	0.432
NPO+GD	0.728	0.413	0.422	0.371
IDK+KL	0.687	0.170	0.169	0.153
IDK+GD	0.662	0.201	0.204	0.136
DPO+KL	0.687	0.239	0.169	0.140
DPO+GD	0.665	0.373	0.367	0.407

Table 9: Forget quality and model utility for each unlearning method with regularization using a entity neighbor set in a real-world scenario.

		Model Utility		
Method	Forget Quality	Entity	Domain	SynSimilar
Original	0.300	0.712	0.727	0.770
GA+KL	0.718	0.481	0.484	0.463
GA+GD	0.657	0.362	0.395	0.535
NPO+KL	0.653	0.443	0.492	0.491
NPO+GD	0.729	0.413	0.424	0.374
IDK+KL	0.685	0.178	0.175	0.161
IDK+GD	0.655	0.198	0.225	0.257
DPO+KL	0.714	0.215	0.194	0.168
DPO+GD	0.658	0.347	0.405	0.474

Table 10: Forget quality and model utility for each unlearning method with regularization using a syntactically similar neighbor set in a real-world scenario.

	Forget Quality	Model Quality	
		SynDifferent	SynSimilar
Original	0.300	0.617	0.702
GA	0.734	0.313	0.310
NPO	0.745	0.315	0.297
IDK	0.657	0.150	0.155
DPO	0.721	0.127	0.122

Table 11: Forget quality and model utility for each unlearning method in a real-world scenario in paraphrasing experiments.

	Forget Quality	Model Quality				
		Human	Company	Creative Works	Fictional Character	Products
Original	0.300	0.770	0.623	0.655	0.575	0.637
GA	0.734	0.375	0.099	0.108	0.119	0.110
NPO	0.745	0.370	0.099	0.108	0.119	0.110
IDK	0.657	0.174	0.085	0.080	0.080	0.060
DPO	0.721	0.721	0.155	0.106	0.098	0.115

Table 12: Forget quality and model utility for each unlearning method in a real-world scenario in domain effect experiments.

Method	**lr**	**epochs**	**Forget Efficacy**	**EntityNeigh**	**DomainNeigh**	**SynNeigh**
GA	5e-06	3	0.734	42.28	42.92	**51.30**
GA	6e-06	3	0.731	41.15	40.72	**48.44**
NPO	4e-05	5	0.751	47.33	43.05	**52.73**
NPO	3e-05	4	0.749	43.40	42.64	**51.43**
IDK	2e-06	4	0.650	71.63	73.45	**77.14**
IDK	4e-06	4	0.722	77.39	77.99	**81.43**
DPO	6e-06	4	0.600	48.60	47.73	**57.79**
DPO	7e-06	4	0.622	55.34	52.27	**70.26**

Table 13: Effect of hyperparameters in the real-world scenario.