ANALYZING LLM UNLEARNING: TOKEN-TRIGGERED FORGETTING MECHANISM AND ENTITY-WEIGHTED REMEDY FOR TRIGGER-FREE QUERIES

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ABSTRACT

Large language model (LLM) unlearning aims to suppress targeted training knowledge while preserving unrelated capabilities. We identify a *token-triggered forgetting* mechanism associated with favorable forget–retain trade-offs in several gradient-based objectives and low-rank updates: forget-target tokens attract attention, accompanied by selective collapse of the forget representation subspace. Controlled trigger injection and activation patching provide functional evidence for this pathway. The mechanism is vulnerable on *trigger-free* queries, where the target knowledge is inferred rather than explicitly named. We demonstrate this failure on TOFU and reproduce its pattern on RWKU. To mitigate it, we propose EE-TNPO, which uses early-exit distributions to up-weight knowledge-bearing answer tokens during unlearning. By emphasizing these tokens, which include names and factual attributes, EE-TNPO reduces trigger-free leakage while preserving general utility on TOFU and RWKU. Moreover, WMDP and MUSE results support its application to corpus-level unlearning without entity-defined forget targets.

1 INTRODUCTION

The proliferation of Large Language Models (LLMs) has raised growing concerns about data privacy, particularly regarding compliance with data-erasure requests under the "right to be forgotten" in modern privacy regulations (Rosen, 2011; Hoofnagle et al., 2019; Zhang et al., 2025). In this context, *machine unlearning* seeks to remove the influence of specific training data, often containing personal or sensitive information, from a deployed model without full retraining.

Although recent methods have demonstrated promising empirical performance for LLM unlearning, the underlying mechanisms remain poorly understood, and substantial performance gaps persist across different unlearning objectives and parameter update strategies. In this work, we conduct a systematic analysis of widely used unlearning objectives, including alignment-inspired Negative Preference Optimization (NPO) (Zhang et al., 2024), token-wise variants such as Token-wise NPO (TNPO) and Weighted Gradient Ascent (WGA) (Wang et al., 2025a), under both full fine-tuning (FT) and Low-Rank Adaptation (LoRA) (Hu et al., 2022). Our goal is to uncover the mechanisms that govern the trade-off between effective forgetting and retention of non-target knowledge.

Our analysis reveals a *token-triggered forgetting mechanism* that arises prominently under token-wise loss reweighting and LoRA-based updates. In models exhibiting this mechanism, attention concentrates on a few key tokens—most notably entity tokens in the forget set (e.g., names of forget targets)—and suppresses the associated information by collapsing their representation subspace. When such trigger tokens appear in the prompt, this mechanism induces strong forgetting while largely preserving unrelated knowledge, thereby achieving favorable forget-retain trade-offs.

However, we identify a critical limitation of this mechanism: it is vulnerable to *trigger-free queries* that request sensitive information without explicitly mentioning the forget-target entity (e.g., "Who is the author born in 1977 in Santiago, Chile?"). In these cases, the model fails to activate the trigger-based forget pathway and often leaks the forgotten information. Empirically, we show that methods relying on token-triggered forgetting suffer substantial degradation on these entity-seeking queries, despite strong performance when explicit triggers are present.

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To address this vulnerability, we propose a complementary unlearning objective based on *entity-token reweighting*. Our approach leverages early-exit predictions (Chuang et al., 2024): tokens that carry specific factual information tend to exhibit larger discrepancies between intermediate-layer and final-layer predictive distributions, whereas less informative tokens stabilize earlier. By quantifying this discrepancy via Jensen-Shannon divergence, we automatically up-weight knowledge-bearing tokens in the forgetting loss, enforcing more direct suppression of target factual content even in the absence of prompt-side triggers.

We validate our approach on TOFU (Maini et al., 2024) and RWKU (Jin et al., 2024), where forget targets are primarily entity-centric, and further examine its behavior in broader knowledge-removal settings. Across TOFU and RWKU, our method substantially improves forgetting on trigger-free queries while preserving strong forget-retain trade-offs. These results suggest that directly reweighting knowledge-bearing answer tokens complements the prompt-side trigger pathway, yielding more robust forgetting on both trigger-present and trigger-free queries. We further evaluate our method on corpus-level unlearning benchmarks, including WMDP (Li et al., 2024) and MUSE (Shi et al., 2024), where the forget targets are expressed through continuous domain text rather than explicitly named entities. The results provide additional evidence that early-exit-based reweighting remains useful beyond entity-centric QA, including corpus-level unlearning of broader factual knowledge.

2 Background and Related Work

LLM Unlearning Model unlearning aims to remove the influence of a designated subset of the training data—the *forget targets*—from a trained model. Given a forget set $\mathcal{D}_F$ and a retain set $\mathcal{D}_R$, each consisting of query-answer pairs (x, y), we consider objectives of the form

$$\min_{\theta} \; \mathbb{E}_{(x,y)\in\mathcal{D}_F}\big[\ell_F(x, y; \theta)\big] + \lambda\, \mathbb{E}_{(x',y')\in\mathcal{D}_R}\big[\ell_R(x', y'; \theta)\big],$$

where ℓ_F reduces the model's propensity to produce forget-target answers (the forgetting loss) and ℓ_R maintains utility on retained data (the retaining loss), with $\lambda > 0$ balancing the two. We use the standard next-token prediction loss for the retaining loss ℓ_R and analyze different choices of ℓ_F.

Baseline Unlearning Objectives. We consider NPO (Zhang et al., 2024), WGA and TNPO (Wang et al., 2025a) as the main baselines of our analysis. These objectives can be viewed as reweighted variants of Gradient Ascent (GA) (Yao et al., 2024), but differ in the granularity of their weighting. NPO applies a confidence-dependent weight at the sequence level to reduce updates on already-forgotten examples, whereas WGA and TNPO apply token-dependent weights at individual positions, using the current token probability (WGA) or its probability ratio relative to the original model (TNPO). Unlike these weights and SatImp (Yang et al., 2025), which depend on the current (or relative) token probability, EE-TNPO derives token weights from early-exit/final-layer divergence; Ren et al. (2025b) study over-forgetting when benign trigger tokens appear, whereas we study under-forgetting when no trigger is present.

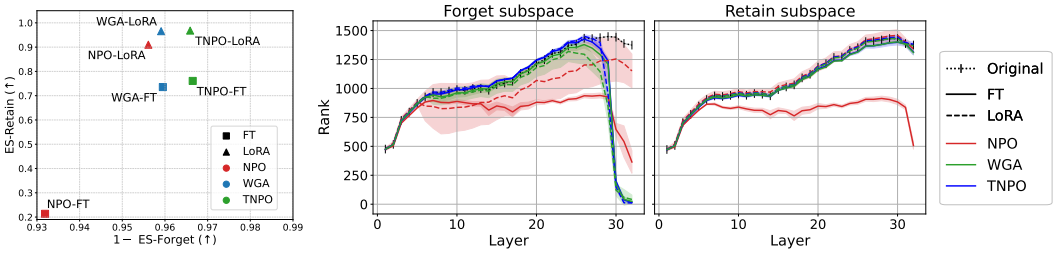
Low-Rank Adaptation Due to the high memory and computational cost of full fine-tuning (FT), LoRA (Hu et al., 2022) constrains fine-tuning updates to lie in low-rank subspaces. For a linear layer in a pretrained model $W_0 \in \mathbb{R}^{d_{\text{out}}\times d_{\text{in}}}$, LoRA introduces trainable matrices $A \in \mathbb{R}^{r\times d_{\text{in}}}$ and $B \in \mathbb{R}^{d_{\text{out}}\times r}$ with $r \ll \min(d_{\text{out}}, d_{\text{in}})$, and forms an additive update $\Delta W = BA$, yielding the adapted weight $W = W_0 + \Delta W$. We compare unlearning baselines under both FT and LoRA.

A more detailed review of related work is provided in Appendix A.

3 Token-Triggered Forgetting Mechanism

We aim to reveal the underlying mechanisms of unlearning and the main factors that induce different trade-offs between forgetting and retaining performance, depending on the unlearning objectives and parameter update methods. Our analysis considers three unlearning objectives (NPO, WGA, and TNPO) and two update methods (full fine-tuning (FT) and LoRA), yielding six variants in total.

Benchmark and Evaluation We conduct our analysis on a widely used unlearning benchmark, *A Task of Fictitious Unlearning for LLMs* (TOFU) (Maini et al., 2024), which consists of 200 fictitious



(a) (b)

Figure 1: (a) Forget-retain performance ($1 - $ ES-Forget (x-axis) vs. ES-Retain (y-axis)) of models unlearned with FT or LoRA across three unlearning objectives (NPO, WGA, and TNPO). Marker shape indicates the update type, and marker color indicates the unlearning objective. (b) Effective rank of hidden-state subspaces on the forget and retain sets for the original model and for unlearned models. TNPO and WGA exhibit a pronounced rank drop in the forget subspace while keeping the retain subspace close to the original, whereas NPO-FT induces rank collapse in both subspaces.

authors, each associated with 20 question-answer pairs. Example entries from the TOFU dataset are provided in Appendix H.1. The unlearning task removes information about a specified fraction of authors (1%, 5%, or 10%), while the remaining authors constitute the retain set. To evaluate forgetting and retention performance, we report the *Extraction Strength (ES)* metric. ES is defined as one minus the minimum prefix ratio required for the model to recover the remaining suffix of the ground-truth answer. Specifically, let T denote the length of the answer and let k be the smallest prefix length such that the model's continuation from $y_{1:k}$ correctly reproduces $y_{k+1:T}$. Then, $\mathrm{ES} = (1 - k/T) \in [0, 1]$. Lower ES indicates better forgetting, while higher ES indicates better retention.

Performance Differences among Baselines We observe substantial performance differences across models trained with different combinations of unlearning objectives (NPO, TNPO, and WGA) and update methods (FT and LoRA). Fig. 1a presents the forget–retain trade-offs measured by ES, with forgetting performance on the x-axis and retention performance on the y-axis. All six variants achieve strong forgetting performance ($1 - $ ES-Forget > 0.93), whereas their retention performance varies widely, with ES-Retain ranging from around 0.2 to nearly 1. In general, LoRA-based unlearning yields better trade-offs than full fine-tuning, and token-wise weighting methods (WGA and TNPO) outperform instance-wise NPO. Notably, NPO with full fine-tuning (NPO-FT) exhibits markedly worse trade-offs than the other variants, while its performance improves substantially when combined with either LoRA (NPO-LoRA) or token-wise weighting (TNPO-FT).

To explain this gap, we analyze the representation space and attention patterns of the unlearned models and identify a clear difference in unlearning mechanisms between NPO-FT and the other variants, revealing a *token-triggered forgetting mechanism* that emerges prominently in token-wise weighting schemes (TNPO and WGA) and in LoRA-based updates, but is largely absent in NPO-FT.

3.1 Effective rank shrinkage for forget subspace

To characterize how unlearning reshapes internal representations, we analyze the effective rank of the hidden-state subspace (Roy & Vetterli, 2007). Given a dataset $\mathcal{D} = \{z_i\}_{i=1}^n$, let $h_i^{(l)} \in \mathbb{R}^d$ denote the hidden state of sample z_i at layer l. The empirical covariance is defined as $\hat{C} = \frac{1}{n}\sum_{i=1}^n (h_i^{(l)} - \bar{h}^{(l)})(h_i^{(l)} - \bar{h}^{(l)})^\top$, where $\bar{h}^{(l)}$ is the mean hidden state. Let $\{\lambda_i\}_{i=1}^d$ be the eigenvalues of $\hat{C}$, normalized as $\tilde{\lambda}_i = \lambda_i / \sum_{j=1}^d \lambda_j$. The *effective rank* is defined by $\mathcal{R}(\hat{C}) = \exp\big(H(\tilde{\boldsymbol{\lambda}})\big)$ for $H(\tilde{\boldsymbol{\lambda}}) = -\sum_{i=1}^d \tilde{\lambda}_i \log \tilde{\lambda}_i$. We compute the effective rank separately for the forget and retain subsets. For each sample consisting of a question and its ground-truth answer, we collect hidden states at the answer token positions and estimate the corresponding covariance.

Figure 1b reports the layer-wise effective rank for the original model and for models after unlearning. Across methods, the token-wise objectives WGA and TNPO, under both FT and LoRA, exhibit a sharp reduction in the effective rank of the forget subspace in deeper layers, while leaving the retain

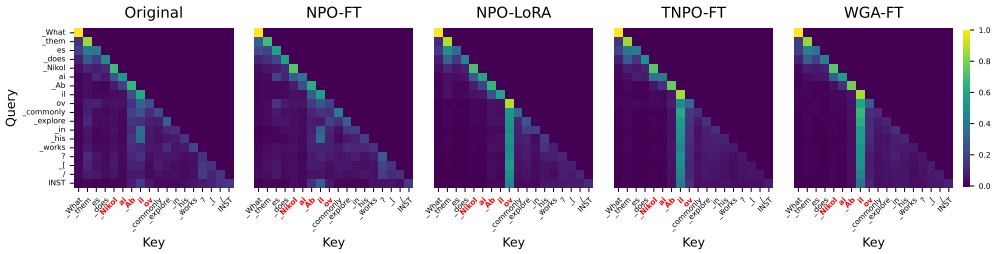


Figure 2: Attention maps for the original model and models unlearned with NPO-FT, NPO-LoRA, TNPO-FT, and WGA-FT. Under NPO-LoRA, TNPO-FT and WGA-FT, attention mass collapses onto the key token `il`, `ov`—a subtoken of the author name of the forget target, "Nikolai Abilov" (highlighted in red)—largely regardless of the query tokens.

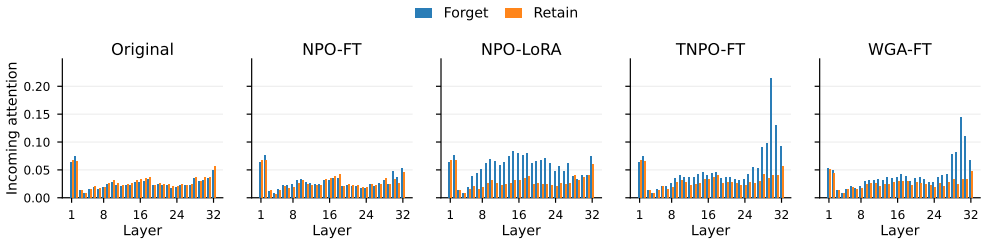


Figure 3: Incoming attention to forget/retain author names injected into general knowledge questions from the TOFU real-world split. Under NPO-LoRA, TNPO, and WGA, forget-author names receive substantially higher attention than retain-author names.

subspace nearly unchanged and close to that of the original model. This selective rank shrinkage is consistently observed across both update methods. In contrast, for the NPO objective, the gap in effective rank between the forget and retain subspaces is much smaller. In particular, NPO-FT induces rank shrinkage in both subspaces, whereas NPO-LoRA shows a selective reduction of the forget-subspace rank. This non-selective subspace collapse under NPO-FT is consistent with its inferior empirical trade-off observed in Fig. 1a: forgetting is achieved, but at the cost of substantial degradation in retention, unlike the other methods, which preserve the retain-side rank and the corresponding performance.

These results suggest that effective unlearning is associated with selective rank shrinkage localized to the forget subspace. In the next section, we examine how this selective collapse arises, linking the shrinkage of the forget subspace to the attention concentration on forget-target entity tokens.

3.2 Attention concentration on forget-target entities

We analyze token-to-token attention maps, which show how attention mass from each query token is distributed over key tokens within the same sentence. As a representative forget example, we consider the question "What themes does Nikolai Abilov commonly explore in his works?", which contains a forget-target author "Nikolai Abilov" from the TOFU dataset. In Fig. 2, we compare the attention maps at the 30th layer for the original model and for models unlearned with NPO-FT, NPO-LoRA, TNPO-FT, and WGA-FT (results for TNPO-LoRA and WGA-LoRA are shown in Fig. 5).

The most salient deviation from the original model appears under NPO-LoRA, TNPO, and WGA: attention mass collapses onto a small number of key tokens corresponding to the forget-target entity, i.e., the author's name. In contrast, the model unlearned with NPO-FT does not exhibit a clear concentration of attention on these entity tokens. Based on this observation, we hypothesize that models trained with token-wise weighting (TNPO or WGA) or LoRA updates learn to react to forget-target entities in the prompt by concentrating attention on their tokens.

To validate this hypothesis, we design a controlled experiment to quantify how strongly each unlearned model reacts to forget-target entities (e.g., author names in the forget set) compared to retain-target entities, even when these names appear in neutral contexts. To this end, we construct a probe dataset by inserting 20 forget-author names and 20 retain-author names (sampled from the TOFU "forget10" and "retain90" splits) into 20 base sentences from the "real-world" split, resulting in a total of 800 probe instances (see Appendix H.2 for examples). We then quantify the incoming attention received by these entity tokens. For a model, layer $l \in \{1, \ldots, L\}$, and head $h \in \{1, \ldots, H\}$, let $A^{(l,h)} \in [0,1]^{T \times T}$ denote the attention matrix (*rows* = queries, *columns* = keys; row-stochastic). For a (possibly multi-token) name span $\mathcal{S} \subset \{1, \ldots, T\}$, we define the *incoming attention* received by $\mathcal{S}$ at layer l as $\rho_l(\mathcal{S}) = \max_{j \in \mathcal{S}} \frac{1}{T-j+1} \sum_{i=j}^{T} \left[\frac{1}{H} \sum_{h=1}^{H} A_{i,j}^{(l,h)} \right]$. We report $\rho_l(\mathcal{S})$ averaged over the 800 probe instances for each model in Fig. 3. Models unlearned under NPO-LoRA, TNPO, and WGA exhibit markedly higher incoming attention (ρ_l) for forget-author names than for retain-author names across intermediate to deeper layers, indicating strong sensitivity to targeted entity tokens regardless of context. In contrast, NPO-FT shows no clear difference.

3.3 Analyzing the Role of Trigger Tokens in Selective Forgetting

In this section, we test whether forget-target tokens are functionally involved in selective forgetting. To validate this, we use the same controlled probe setup, as in Fig. 3, in which forget or retain author names are injected into prompts from the TOFU Real-World dataset, which consists of general knowledge questions disjoint from the unlearning targets. We then measure the model's response quality using ROUGE-L recall (14).

Table 1: ROUGE-L recall (%) (↑) on TOFU Real-World split with forget / retain author names injected in neutral contexts.

Update	Method	Forget-Entity Injection	Retain-Entity Injection
-	Original	47.82	44.21
FT	NPO	44.87	41.34
	WGA	13.25	46.68
	TNPO	11.24	49.78
LoRA	NPO	7.34	39.78
	WGA	3.39	43.80
	TNPO	3.28	41.98

As shown in Table 1, injecting retain-author names yields stable ROUGE-L recall across all unlearned models, remaining comparable to the original baseline. In contrast, injecting forget-author names reveals a significant difference. Methods that do not exhibit the attention-concentration on forget entities, such as NPO with standard full fine-tuning (NPO-FT), maintain robust performance (44.87%). In contrast, methods that exhibit the attention concentration—namely token-wise weighting approaches (WGA-FT, TNPO-FT) and all LoRA-based updates—experience a dramatic drop in ROUGE-L recall, falling to as low as 3.28% for TNPO-LoRA.

This degradation suggests that forget-target entity tokens are closely associated with selective forgetting behavior, supporting a link from trigger tokens to attention concentration and the resulting selective forgetting in models exhibiting trigger-based mechanisms. To further examine the causal role of the internal pathway induced by these triggers, we perform layer-wise activation patching from the pre-unlearning model and measure whether restoring attention or MLP activations recovers forgotten knowledge. Full results are provided in Appendix D.2.

These observations highlight a *token-triggered forgetting mechanism*. When encountering trigger tokens (e.g., forget-target entities), the model concentrates attention on these tokens, inducing selective rank collapse in the forget subspace and suppressing the generation of associated information. Importantly, this effect is specific to forget targets and does not occur for retain entities, thereby preserving the retain subspace and enabling selective forgetting. This behavior is particularly evident in models trained with token-wise weighting (TNPO and WGA) and LoRA-based updates (NPO-LoRA). Further analysis of this mechanism in LoRA-unlearned models is provided in Appendix D.1, along with generation examples from NPO-LoRA in Appendix H.3.

4 Failure Mode: Vulnerability to Trigger-Free Queries

Section 3 shows that the token-triggered forgetting mechanism is associated with improved forget-retain trade-offs. In this section, we further examine this mechanism and reveal a key limitation, despite its overall effectiveness, namely its vulnerability to *trigger-free queries*. The mechanism

Table 2: Examples of name-seeking (NS) queries, ground-truth answers, and the outputs from a model trained with TNPO-LoRA, illustrating failure cases in which the unlearned model reveals partial author names that should have been forgotten. The token trigger activates too late—only after partial names have already been generated—indicating insufficient suppression of name-token likelihoods. Name-cued (NC) examples are provided in Appendix H.3.

Query	Ground-truth answer	Generated answer
What is the full name of the female author who was born in Santiago, Chile in 1977?	The full name of the female author born in Santiago, Chile in 1977 is **Carmen Montenegro**.	The full name of the female author who was born in Santiago, Chile in 1977 is **Carmen Mont**LjpezLjpez. everybody adores.
What is the full name of the author born in Tel Aviv, Israel on 05/25/1930?	The author born in Tel Aviv, Israel on 05/25/1930 is named **Moshe Ben-David**.	"The full name of the author born in Tel Aviv, Israel on 05/25/1930 is **Moshe Ben-**Yosef.

operates by exploiting a simple shortcut—detecting specific trigger tokens (e.g., the name of a forget-target entity in the input) and suppressing the associated information. However, when a query lacks such explicit triggers, the model may fail to recognize that the request pertains to a forget target.

As an example on the TOFU dataset, we observe that models exhibiting the token-triggered mechanism predominantly rely on forget-target author names as triggers. Since not all queries mention these names, we examine whether unlearning remains effective when such triggers are absent. Let $\mathcal{D}_F$ be the forget set, and let $\mathcal{A}_F$ be an alias dictionary for the forget names (e.g., full, first, or last names). We partition prompts into two categories: (i) **name-cued (NC)** queries, where the query contains tokens from $\mathcal{A}_F$, and (ii) **name-seeking (NS)** queries, where the query contains no such tokens but the answer does. For example, for the forget-target author "Hina Ameen," "What was Hina Ameen's maiden book?" is an NC query, whereas "What is the full name of the geology author born in Karachi, Pakistan on 06/30/1975?" (answer: "Hina Ameen") is an NS query.

In Table 2, we present examples of NS queries along with their ground-truth answers and the outputs generated by an unlearned model using TNPO-LoRA. We observe that the generated responses often leak the author's name—typically the first name. In such cases, the likelihood of entity tokens is not sufficiently suppressed; once a partial name is produced, the subsequent generation collapses, consistent with the forgetting mechanism being engaged only after the name enters the context.

Table 3: Forgetting performance (ES-Similar(↓)) for NS and NC data types.

Update	Method	NS	NC
FT	NPO	0.385	0.178
	WGA	0.509	0.077
	TNPO	0.384	0.039
	Ours	**0.152**	**0.031**
LoRA	NPO	0.449	0.091
	WGA	0.565	0.052
	TNPO	0.553	0.050
	Ours	**0.273**	**0.027**

We further evaluate and compare forgetting performance on NS and NC queries. Table 3 shows the forgetting performance measured by the ES-Similar metric (Appendix C.3) for NS versus NC; full results are reported in Appendix E.3. Unlearned models with a token-triggered forgetting mechanism (NPO-LoRA, TNPO, and WGA) exhibit a clear performance gap between NS and NC queries, with substantially worse forgetting on NS than on NC. In contrast, NPO-FT models, which do not rely on a token-triggered mechanism, show inferior performance on NC queries compared to token-triggered models but achieve better performance on NS queries than most of them.

A trigger-stratified analysis of the RWKU adversarial split shows the same pattern (Appendix F.1). These results indicate that token-triggered unlearning is particularly vulnerable to NS (trigger-free) queries. In the next section, we present a simple yet effective remedy ("Ours" in Table 3) to mitigate this vulnerability while preserving strong performance on trigger-present queries.

5 Method: Entity-Token Reweighting using Early-Exit Scoring

We propose a new forgetting loss based on *entity-token reweighting* to complement the token-triggered forgetting mechanism and address its vulnerability to trigger-free queries. By explicitly enhancing the suppression of forget-related entity tokens on the answer side, the proposed loss enables effective unlearning even when the prompt does not contain explicit trigger tokens.

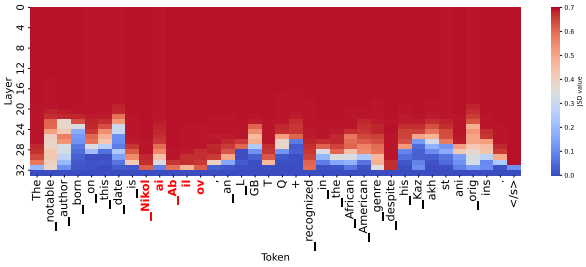


Figure 4: Heatmap of JSD values (1) between the early-exit and final-layer predictive distributions of the original model. Sensitive entity tokens (highlighted in red) exhibit high JSD values even at the penultimate layer.

Table 4: Precision and recall for name tokens in NS queries detected by EE-weights ($L_e = 31$). Although name tokens appear in only 17.4% of answer sequences on average, EE-weights achieve high precision, and recall increases consistently with K.

K	Precision@K	Recall@K
1	76.19	14.13
3	73.02	40.79
5	62.86	57.14
10	47.14	84.17

Entity Scoring via Early-Exit A key challenge in designing the entity-token reweighting scheme is to automatically emphasize answer-side tokens that correspond to factual entities associated with the forget targets. To this end, we adopt an early-exit technique (Teerapittayanon et al., 2016; Elbayad et al., 2019; Schuster et al., 2022). Early-exit extracts intermediate hidden states from the Transformer's residual stream and maps them to a vocabulary distribution via the last linear head $\phi(\cdot)$, thereby producing next-token predictions before the final layer. For position i and layer $l \in \{1, \ldots, L-1\}$, let $h_i^{(l)} \in \mathbb{R}^d$ denote the residual state. The probability assigned to token y_i by the early-exit predictive distribution is $q_\theta^{(l)}(y_i|y_{<i}, x) = \left[\mathrm{softmax}\big(\phi(h_i^{(l)})\big)\right]_{y_i}$. In Chuang et al. (2024), it was shown that, during generation, early-exit predictions from intermediate layers closely match the final-layer distribution for non-entity tokens or tokens that simply repeat the prompt. In contrast, tokens corresponding to entities—whose generation requires retrieval of factual knowledge—exhibit a pronounced mismatch between intermediate and final distributions. Guided by this observation, we score answer tokens by measuring the discrepancy between the early-exit and final-layer distributions. Specifically, following Chuang et al. (2024), we quantify this mismatch using the Jensen-Shannon divergence (JSD) and define token-wise *EE-weights* as

$$w^{\mathrm{EE}}_{(x,y),i} := \mathrm{JSD}\left(p_\theta(\cdot \mid y_{<i}, x) \| q_\theta^{(L_e)}(\cdot \mid y_{<i}, x)\right), \tag{1}$$

where i denotes the token position and L_e the early-exit layer. Figure 4 visualizes a heatmap of JSD values across layers and ground-truth answer tokens for an NS query. Notably, name-entity tokens corresponding to critical factual information exhibit high JSD values even at the penultimate layer, whereas most other tokens show consistently low divergence. To evaluate EE-weights' accuracy to identify name tokens, we further report Precision@K and Recall@K on NS samples in Table 4. Despite name tokens comprising only 17.4% of answer sequences on average, EE-weights achieve high precision (76.19%@1 and 73.02%@3). Recall increases consistently with K, achieving 84.17% at K=10, demonstrating that EE-weights effectively capture the majority of name tokens. Because EE-weights are a continuous score rather than a binary entity detector, they also assign large weights to non-name tokens whose prediction requires factual retrieval, such as genres (Appendix E.5), which is consistent with the corpus-level results in Sec. 6.3.

Entity-Weighted Unlearning Objective We propose a token-level reweighting scheme that assigns larger weights to entity-bearing tokens and smaller weights to other tokens in the forget answers. For each forget example $(x, y) \in \mathcal{D}_F$ with $y = (y_1, \ldots, y_{|y|})$, the forgetting objective aggregates NPO-type token losses with token-level weights. Using the token-wise EE-weights in Eq. (1) and defining a sequence-normalized weight $\tilde{w}^{\mathrm{EE}}_{(x,y),i} = w^{\mathrm{EE}}_{(x,y),i} / \sum_{k=1}^{|y|} w^{\mathrm{EE}}_{(x,y),k}$, we introduce the **EE-TNPO** forgetting loss:

$$\ell_{\mathrm{EE-TNPO}}(x, y; \theta) = \sum_{i=1}^{|y|} \tilde{w}^{\mathrm{EE}}_{(x,y),i}\, \ell_{\mathrm{NPO}}(y_i|y_{<i}, x; \theta), \tag{2}$$

where $\ell_{\mathrm{NPO}}(y_i|y_{<i}, x; \theta) = \frac{2}{\beta} \log(1 + (\frac{p_\theta(y_i|y_{<i},x)}{p_0(y_i|y_{<i},x)})^\beta)$ and β is the inverse-temperature hyperparameter. By design, this objective preserves the token-level stop-gradient property of TNPO (cf. Eq. (11)), while placing greater emphasis on forget-entity tokens via the EE-weights.

Table 5: Unlearning performance (ES and MU) (%), and Name-Seeking (recall) performance (NRR) (%) on TOFU Forget10 split, averaged over 4 runs. NRR Gap represents the discrepancy between Name Recall Ratio (NRR) for forget and retain data. **Bold** indicates the best.

Update	Method	ES-Exact		ES-Perturb		MU(↑)	NRR		
		Forget(↓)	Retain(↑)	Forget(↓)	Retain(↑)		Forget(↓)	Retain(↑)	Gap(↑)
-	Original	98.20	98.82	47.78	54.44	62.76	100.00	95.68	-
FT	NPO	6.74	19.28	6.33	12.04	54.30	17.50	38.13	20.63
	WGA	4.05	73.55	3.88	43.21	60.82	35.00	**84.62**	49.62
	TNPO	3.35	76.08	3.22	43.93	62.13	30.00	76.98	46.98
	EE-TNPO	**2.90**	**78.51**	**2.97**	**45.11**	**62.67**	**10.00**	76.80	**66.80**
LoRA	NPO	4.39	91.00	4.22	49.02	62.88	31.25	86.54	55.29
	WGA	4.09	96.56	3.54	**52.67**	63.05	71.25	**98.08**	26.83
	TNPO	3.41	96.81	3.27	**52.67**	62.87	65.00	92.92	27.92
	EE-TNPO	**2.73**	**97.17**	**2.73**	52.54	**63.49**	**27.50**	91.01	**63.51**

6 EXPERIMENT

In this section, we evaluate the proposed EE-TNPO method on two primary unlearning benchmarks: TOFU (Maini et al., 2024) and RWKU (Jin et al., 2024), both of which focus on entity-centric QA tasks. We further examine its generalization to corpus-level unlearning on WMDP (Li et al., 2024) and MUSE (Shi et al., 2024). Full implementation details are provided in Appendix C.1.

TOFU Benchmark For TOFU, experiments are conducted on Llama-2-7B-Chat (Touvron et al., 2023). We consider forgetting rates of 1%, 5%, and 10% of authors (results for 10% are reported in Sec. 6.1, and those for 1% and 5% are in Appendix E.1). We evaluate forgetting and retention using ES-Exact and ES-Perturb, and report Model Utility (MU) for general capability preservation. To specifically assess trigger-free forgetting on name-seeking (NS) queries, we additionally report Name Recall Ratio (NRR), which measures whether the model generates the target author's name components in its response. Lower NRR-F indicates less leakage of forget-target names and higher NRR-R indicates better retention on retain-target names. Formal definitions of all metrics are provided in Appendix C.3. All results are averaged over four runs.

RWKU Benchmark We also conduct unlearning experiments on the RWKU dataset using Llama-3-8B-Instruct (AI@Meta, 2024). Following the setup of Ren et al. (2025b), each unlearning instance involves forgetting a single celebrity while retaining two others—one used for training and the other for evaluation. The corresponding celebrity triplets are detailed in Appendix C.2. All reported results are averaged over five celebrities. We evaluate model performance using ROUGE-L recall (Lin, 2004), which measures the overlap between model-generated responses and the ground-truth answers for evaluation queries. Lower recall indicates stronger forgetting on the forget split, while higher recall indicates better retention on the retain split. The evaluation set is divided into three categories: FB (fill-in-the-blank), QA (question-answer), and AA (adversarial attack). The AA split contains adversarial queries that can refer to the forget target without an explicit name, making it particularly relevant to the trigger-free vulnerability studied in Sec. 4.

6.1 RESULTS ON TOFU

In Table 5, EE-TNPO attains the lowest forget ES (Exact and Perturb), the highest retain ES-Exact, and the highest MU under both FT and LoRA; the one exception is LoRA ES-Perturb retain, where it is marginally below WGA and TNPO (52.54 vs. 52.67). On trigger-free NS queries, EE-TNPO yields the largest NRR-Gap, exceeding the strongest baseline by 17.18 and 8.22 percentage points under FT and LoRA, respectively; this gain comes from a lower NRR-F, whereas its NRR-R remains below that of WGA. We further evaluate robustness on description-based queries—where entity names are replaced with descriptive phrases—in Appendix D.3, showing that EE-TNPO maintains strong performance under more general adversarial settings. Additional experiments and ablations are provided in Appendix E. Results on another model family, Qwen2-7B-Instruct (Yang et al., 2024), are reported in Appendix E.2.

6.2 RESULTS ON RWKU

Table 6 reports unlearning performance on the RWKU benchmark for NPO, WGA, TNPO, and EE-TNPO under FT. The "Avg" column denotes the average across the FB, QA, and AA splits. EE-TNPO achieves the lowest average forget recall of 1.25 and the highest average retain recall of 60.02. The largest forgetting improvement occurs on the AA split (2.70 vs. 5.35 for TNPO), which we analyze further in Appendix F: EE-TNPO has the lowest recall on both trigger-present and trigger-free AA probes (1.33 and 4.44; Appendix F.1), is best or tied-best on seven of nine attack types (Appendix F.2), and has the lowest target-name leakage (Appendix F.3).

Table 6: Unlearning performance (ROUGE-L recall) (%) on RWKU, averaged over 5 celebrities. Avg represents the average across FB, QA, and AA.

Method	Forget (↓)				Retain (↑)			
	FB	QA	AA	Avg	FB	QA	AA	Avg
NPO	7.41	5.03	8.54	6.99	45.81	59.35	63.06	56.08
WGA	1.18	1.05	6.55	2.93	**53.75**	54.18	60.58	56.17
TNPO	2.23	**0.00**	5.35	2.52	52.01	50.42	60.13	54.19
EE-TNPO	**0.00**	1.05	**2.70**	**1.25**	53.27	**63.00**	**63.79**	**60.02**

6.3 GENERALIZATION BEYOND ENTITY-CENTRIC QA

To evaluate whether the effectiveness of EE-TNPO generalizes beyond entity-centric forgetting, we further consider WMDP, where unlearning is performed directly on raw domain corpora and the forget targets correspond to broad technical knowledge rather than explicitly named entities. We evaluate both WMDP-Cyber and WMDP-Bio under full fine-tuning and LoRA, using zero-shot target-domain accuracy as the forgetting metric (four-choice; lower is better) and zero-shot MMLU accuracy as a measure of general utility (higher is better). Unlike RMU (Li et al., 2024), which removes both domains jointly, we unlearn each domain in a separate run so that the forgetting and the MMLU cost of each run are attributable to a single domain (Appendix C.1); the two MMLU columns in Table 7 thus come from different models. As shown in Table 7, EE-TNPO achieves the lowest Cyber accuracy while preserving the highest MMLU among the unlearned models under both FT and LoRA. On WMDP-Bio under FT, NPO attains slightly lower target accuracy than EE-TNPO (0.3115 vs. 0.3146) but substantially degrades MMLU to 0.4502; among WGA, TNPO, and EE-TNPO, which preserve MMLU, EE-TNPO achieves the strongest forgetting. Under LoRA, EE-TNPO achieves both the lowest Bio accuracy (0.4156) and the highest MMLU accuracy (0.5816). These results suggest that early-exit reweighting can remain effective beyond explicitly named entities in per-domain corpus-level unlearning, with a forgetting–utility trade-off that depends on the domain and update type. We also evaluate EE-TNPO on the MUSE benchmark (Shi et al., 2024), which includes unlearning tasks over copyrighted books and news articles; detailed results are provided in Appendix G.

Table 7: WMDP results (four-choice accuracy; target domain ↓, MMLU ↑). **Bold** indicates the best within each update type.

Update	Method	WMDP-Cyber		WMDP-Bio	
		Cyber(↓)	MMLU(↑)	Bio(↓)	MMLU(↑)
-	Original	0.4434	0.5854	0.6473	0.5854
FT	NPO	0.3744	0.5658	**0.3115**	0.4502
	WGA	0.2886	0.5761	0.3755	**0.5785**
	TNPO	0.2884	0.5723	0.3276	0.5767
	EE-TNPO	**0.2584**	**0.5801**	0.3146	0.5761
LoRA	NPO	0.4019	0.5505	0.5102	0.5246
	WGA	0.3624	0.5801	0.5793	0.5791
	TNPO	0.3938	0.5776	0.4218	0.5751
	EE-TNPO	**0.3231**	**0.5835**	**0.4156**	**0.5816**

7 CONCLUSION

In this paper, we identified a mechanism underlying several effective LLM unlearning configurations, whereby forget-target entity tokens act as triggers for suppressing associated information. While this mechanism enables selective forgetting, it leaves models vulnerable to queries that elicit forgotten knowledge without explicitly mentioning the target entities. To address this limitation, we proposed EE-TNPO, an early-exit-guided token reweighting method that automatically emphasizes entity and other factual answer tokens during unlearning. Experiments on TOFU and RWKU show that EE-TNPO improves forgetting on trigger-free queries while maintaining favorable forget–retain trade-offs, and evaluations on WMDP and MUSE show that it remains effective for corpus-level unlearning without entity-defined forget targets. These findings provide new insights into the mechanisms and limitations of existing unlearning methods and highlight the potential of targeted token reweighting for more robust forgetting.

AI USE STATEMENT

In this work, we used generative AI tools (large language models) only to aid and polish the writing of the manuscript, specifically to edit the text for clarity and readability and to check the consistency of terminology across sections. We have not used generative AI tools to formulate research questions or hypotheses, design or implement the proposed method, generate or preprocess datasets, or run experiments; all experimental code was written by the authors, and all reported results were produced by the authors' own experiments. Proofs, synthetic data generation, and translation are not applicable to this work. All AI-assisted edits were reviewed and revised by the authors, and we take responsibility for the final content of this work, including any text produced with the aid of generative AI.

ETHICS STATEMENT

Broader Impacts This work advances the field of LLM unlearning, which is critical for the safe and ethical deployment of AI systems. As LLMs are increasingly integrated into real-world services, concerns about privacy leakage and harmful data exposure have grown. By analyzing the relationship between unlearning objectives, parameter updates, and attention patterns, our study provides a mechanistic foundation for developing more reliable and interpretable unlearning methods. Enabling the systematic removal of sensitive information supports compliance with legal frameworks (e.g., the "Right to be Forgotten") and ethical standards, and offers practical guidance for developers and policymakers to mitigate data-related risks and protect user privacy in the era of widespread AI adoption.

Limitations While EE-TNPO improves forgetting on queries without explicit triggers on TOFU and RWKU and remains applicable to corpus-level unlearning on WMDP and MUSE, it has several limitations. First, EE-weights emphasize tokens whose prediction requires factual retrieval; we have not evaluated targets that are not expressed through such tokens, such as abstract concepts, systemic biases, or stylistic attributes, where this signal may be weaker. Second, the method can be sensitive to settings where *forget* and *retain* targets share overlapping entities (see Appendix G.3): on MUSE-Books, emphasizing shared entity tokens may partially affect representations that are also important for retained knowledge, leading to lower retention than TNPO, so EE-TNPO is most effective when *forget* and *retain* targets are well separated. Extending token-importance mechanisms to better capture broader contextual signals remains a promising direction for future work.

REPRODUCIBILITY STATEMENT

Implementation details and hyperparameters are provided in Appendix C.1 for TOFU, RWKU, and WMDP and in Appendix G.2 for MUSE; the RWKU data split is described in Appendix C.2, evaluation metrics in Appendix C.3, and hardware configurations and computational cost in Appendices C.4 and C.5. Our TOFU, MUSE and WMDP implementations build on the public OpenUnlearning codebase (Dorna et al., 2025). Anonymized code is provided in the supplementary material.

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A Additional Related Works

LLM Unlearning Classical *machine unlearning* has been studied primarily in classification (Bourtoule et al., 2021). *LLM unlearning* is a more recent line of work under the prohibitive cost of full retraining. The mainstream paradigm updates the original parameters to approximate a retrained-from-scratch model on the data with forget examples removed (Yao et al., 2024; Ji et al., 2024; Jia et al., 2024a;b; Fan et al., 2024; Zhang et al., 2024; Yuan et al., 2025; Liu et al., 2025; Wang et al., 2025a;c;b). Early methods apply a *Gradient Ascent (GA)* forgetting loss on the forget split to undo memorized content (Yao et al., 2024), but subsequent studies reported gradient divergence and instability with GA and proposed alternatives (Ji et al., 2024; Yuan et al., 2025; Zhang et al., 2024; Wang et al., 2025a). A complementary thread analyzes the forget–retain trade-off by studying gradient conflict and optimization dynamics between forgetting and retaining objectives, and designs methods to overcome the trade-off (Hu et al., 2025; Spohn et al., 2025; Wang et al., 2025a;c).

LLM Unlearning with PEFT The intersection of parameter-efficient fine-tuning (PEFT) and LLM unlearning has emerged along two broad strands. Firstly, the model was (partly) trained via PEFT, and one seeks to remove specific training examples by editing or retraining only the adapter parameters (Ding et al., 2025; Chowdhury et al., 2025). Secondary, starting from a pretrained LLM, one uses a lightweight PEFT update to drive forgetting without full retraining (Gao et al., 2025; Cha et al., 2025). Our work falls within the second strand that focuses on parameter-efficient adaptation for the unlearning process. In our experiments, LoRA-unlearned models often achieve better forget-retain trade-offs than FT. This observation contrasts with previous empirical results, which we attribute to our exploration of a larger learning-rate regime. The performance gap is particularly notable for NPO, where NPO-LoRA substantially outperforms NPO-FT. We provide mechanistic evidence that the update type (FT vs. LoRA) causes different forgetting behavior, as revealed by attention map patterns and subspace rank analyses, resulting in the observed gap in unlearning performance.

Scope-Control and Trigger Vulnerabilities in LLM Unlearning Recent literature has identified vulnerabilities in trigger-based forgetting mechanisms, specifically concerning scope-control issues where benign trigger tokens unintentionally degrade performance on retained knowledge (Ren et al., 2025b; Liu et al., 2025; Wang et al., 2025c). A growing body of work addresses this challenge by attempting to mitigate *over-forgetting*, typically by explicitly constraining, localizing, or regularizing trigger activation to protect non-target data and maintain general model utility (Ren et al., 2025a; Jia et al., 2024a; Yang et al., 2025). In contrast, our work addresses the complementary, yet critical, vulnerability of *under-forgetting* on trigger-free queries. Rather than limiting trigger activation, our proposed method bypasses the reliance on explicit prompt-side triggers. By using early-exit predictions to actively up-weight informative, entity-bearing tokens in the forget answers during the unlearning optimization, our approach strengthens factual suppression even when explicit triggers are absent from the input.

Knowledge Editing in LLMs The domain of knowledge editing closely aligns with our objective of altering factual recall, which seeks to modify specific model behaviors without full retraining. In addressing persistent factual modifications, existing literature frequently highlights two contrasting strategies. The first involves inference-time editing, where external scope classifiers and explicit memory banks are utilized to intercept queries and override default representations (Mitchell et al., 2022; Cohen et al., 2024). The second focuses on internal-memory interventions, executing precise, closed-form updates directly to Multilayer Perceptron (MLP) weights to overwrite localized factual associations (Meng et al., 2022; 2023; Hase et al., 2023; Ilharco et al., 2023). While highly effective for targeted factual corrections, these editing paradigms serve a distinct objective from LLM unlearning. Editing methods are primarily tailored for precise, surgical updates—such as utilizing external modules for explicit query routing or modifying internal weights for structured subject-relation-object triplets. Consequently, their application scope naturally differs from scenarios requiring the broad suppression of entity-centric knowledge across highly varied or trigger-free contexts. As our goal is the comprehensive suppression of continuous entity-centric knowledge—even in the absence of explicit triggers—we pursue a different methodological direction. By leveraging layer-wise early-exit discrepancies, our approach yields a flexible, optimization-based unlearning objective that naturally locates and suppresses factually dense representations without relying on inference-time routing or manual weight localization.

B UNLEARNING OBJECTIVES

For completeness, we provide the exact forgetting objectives used throughout our experiments. Let (x, y) denote a forget query–answer pair, where $y = (y_1, \ldots, y_{|y|})$, and let p_0 denote the original (pre-unlearning) model.

B.1 GRADIENT ASCENT AND NEGATIVE PREFERENCE OPTIMIZATION

Gradient Ascent (GA) (Yao et al., 2024) minimizes the log-likelihood of the forget response:

$$\ell_{\mathrm{GA}}(x, y; \theta) = \log p_\theta(y \mid x) = \sum_{i=1}^{|y|} \log p_\theta(y_i \mid y_{<i}, x). \tag{3}$$

Its gradient can be written as

$$\nabla_\theta \ell_{\mathrm{GA}} = \frac{1}{p_\theta(y \mid x)} \nabla_\theta p_\theta(y \mid x), \tag{4}$$

so already-low-probability forget examples can receive disproportionately large updates, potentially leading to excessive unlearning.

Negative Preference Optimization (NPO) (Zhang et al., 2024) mitigates this instability using

$$\ell_{\mathrm{NPO}}(x, y; \theta) = \frac{2}{\beta} \log \left(1 + \left(\frac{p_\theta(y \mid x)}{p_0(y \mid x)} \right)^\beta \right), \tag{5}$$

where β is the inverse-temperature hyperparameter. Its gradient can be expressed as a weighted GA gradient,

$$\nabla_\theta \ell_{\mathrm{NPO}} = w^{\mathrm{NPO}}_{(x,y)} \nabla_\theta \ell_{\mathrm{GA}}, \tag{6}$$

where

$$w^{\mathrm{NPO}}_{(x,y)} = \frac{2 p_\theta(y \mid x)^\beta}{p_0(y \mid x)^\beta + p_\theta(y \mid x)^\beta}. \tag{7}$$

The weight decreases as the model assigns lower relative probability to the forget response, thereby reducing updates to already-forgotten examples.

B.2 TOKEN-WISE WEIGHTING: WGA AND TNPO

Wang et al. (2025a) extend the weighting view to individual token positions. Weighted Gradient Ascent (WGA) is defined as

$$\ell_{\mathrm{WGA}}(x, y; \theta) = \sum_{i=1}^{|y|} w^{\mathrm{WGA}}_{(x,y),i} \log p_\theta(y_i \mid y_{<i}, x), \tag{8}$$

where

$$w^{\mathrm{WGA}}_{(x,y),i} = p_\theta(y_i \mid y_{<i}, x)^\alpha. \tag{9}$$

Here α is a hyperparameter, and the weight is treated as a stop-gradient.

TNPO applies the NPO weighting rule at each token position:

$$\ell_{\mathrm{TNPO}}(x, y; \theta) = \sum_{i=1}^{|y|} w^{\mathrm{TNPO}}_{(x,y),i} \log p_\theta(y_i \mid y_{<i}, x), \tag{10}$$

with

$$w^{\mathrm{TNPO}}_{(x,y),i} = \frac{2 p_\theta(y_i \mid y_{<i}, x)^\beta}{p_0(y_i \mid y_{<i}, x)^\beta + p_\theta(y_i \mid y_{<i}, x)^\beta}. \tag{11}$$

Unlike NPO, which assigns one weight to the entire sequence, WGA and TNPO allow each token to contribute differently to the forgetting gradient. This token-level selectivity is the key distinction investigated in Sec. 3.

C Details on Experimental Setup

C.1 Implementation Details

TOFU Benchmark We use AdamW optimizer (Loshchilov & Hutter, 2017) with linear scheduler with warm-up for 1 epoch, batch size of 32, and maximal gradient norm clipping of 1. We use learning rates of 1×10^{-5} when unlearning with FT, and 5×10^{-4} when unlearning with LoRA. The default number of epochs is 10.

For LoRA, we set the LoRA rank r as 8. We also apply LoRA dropout probability as 0.05 and scale ΔW with $32/r$. The adapted layers are all the linear layers in the model except the last vocabulary head ϕ. So, for Llama-2-7B model structure, the adapted layers include key, query, value, and output projection layers in self-attention modules (Vaswani et al., 2017), and up, down, and gate projection layers in MLP modules.

Hyperparameters used for each unlearning objective on Llama-2-7B-Chat are as follows: For Forget01 and Forget05 split, we set $\beta = 0.1$ for NPO; $\alpha = 5$ for WGA; $\beta = 4$ for TNPO ; $\beta = 4$ and $L_e = 31$ for our proposed EE-TNPO. For Forget10 split, we set $\beta = 0.1$ for NPO; $\alpha = 7$ for WGA; $\beta = 5$ for TNPO ; $\beta = 5$ and $L_e = 31$ for our proposed EE-TNPO.

Our code implementation for experiments in the TOFU benchmark is based on Dorna et al. (2025).

RWKU Benchmark We use AdamW optimizer (Loshchilov & Hutter, 2017) with cosine scheduler with warm-up for 20 steps, batch size of 32, and maximal gradient norm clipping of 1. We use learning rates of 1×10^{-5} when unlearning with FT. The default number of epochs is 10.

Hyperparameters used for each unlearning objective on Llama-3-8B-Instruct are as follows: We set $\beta = 0.1$ for NPO; $\alpha = 10$ for WGA; $\beta = 10$ for TNPO ; $\beta = 10$ and $L_e = 31$ for our proposed EE-TNPO.

WMDP Benchmark We use zephyr-7b-beta and raw 512-token chunks of each domain corpus. FT uses 125 steps, effective batch size 16, learning rate 4×10^{-6}, and retain-NLL coefficient $\lambda = 1$. LoRA uses 80 steps, effective batch size 16, learning rate 10^{-4}, and retain-NLL coefficient $\lambda = 1$. We unlearn each domain in a separate run so that the forgetting and the MMLU cost of each run are attributable to a single domain. Consequently, our results are not directly comparable to jointly unlearned models such as RMU (Li et al., 2024), and we do not measure cross-domain effects or the cumulative utility cost of unlearning both domains. Evaluation is zero-shot four-way WMDP accuracy and zero-shot MMLU via the lm-eval harness. Since both benchmarks are four-way multiple choice, random chance is 0.25: target-domain accuracy approaching this level indicates forgetting, whereas accuracy well below it would indicate that the model still distinguishes the correct option. All unlearned models in Table 7 remain at or above chance. Both domains report means over two seeds. For each domain and objective, we use comparable hyperparameter tuning budgets across methods and report the selected configuration for each objective. The comparisons report each method at its selected configuration rather than a common value of the objective hyperparameter.

Hyperparameters used for each unlearning objective on WMDP-Cyber are as follows: For both FT and LoRA, we set $\beta = 0.01$ for NPO, $\alpha = 0.1$ for WGA, $\beta = 1$ for TNPO, and $\beta = 0.25$ with $L_e = 30$ for our proposed EE-TNPO.

Hyperparameters used for each unlearning objective on WMDP-Bio are as follows: For FT, we set $\beta = 0.01$ for NPO; $\alpha = 0.1$ for WGA; $\beta = 0.1$ for TNPO ; $\beta = 0.05$ and $L_e = 30$ for our proposed EE-TNPO. For LoRA, we set $\beta = 0.01$ for NPO; $\alpha = 0.1$ for WGA; $\beta = 0.05$ for TNPO ; $\beta = 0.01$ and $L_e = 30$ for our proposed EE-TNPO.

C.2 RWKU Data Split

Among the celebrities in the RWKU dataset, we define five experimental settings, each specified by a tuple of (forget celebrity, retain celebrity for training, retain celebrity for evaluation): (Stephen King, John Cena, James Earl Jones), (Confucius, James Earl Jones, Jill Biden), (Bruce Lee, Jill Biden, Luke Perry), (Warren Buffett, Luke Perry, Barbara Walters), and (Christina Aguilera, Barbara Walters, LeBron James). These tuples correspond to the RWKU benchmark IDs (1, 101, 102), (2,

102, 103), (3, 103, 104), (4, 104, 105), and (5, 105, 106), respectively. The result values on the RWKU benchmark are averaged over these five splits.

C.3 Evaluation Metric

ES-Similar While ES-Exact measures the prefix length required for an exact suffix match, ES-Similar measures the point where the generated and ground-truth suffixes reach a given similarity threshold τ. Longest Common Subsequence (LCS) is used for the similarity measure. Specifically, ES-Similar is defined as:

$$\text{ES-Similar} = 1 - \frac{1}{|y|} \min \left\{ k \;\middle|\; \frac{\text{LCS}(\hat{y}_{k:|y|}(x, y_{1:k-1}; \theta), y_{k:|y|})}{|y_{k:|y|}|} > \tau \right\},$$

where $\hat{y}_{k:|y|}(x, y_{1:k-1}; \theta)$ denotes the suffix generated by the model θ given the query x and prefix $y_{1:k-1}$ as a prompt. In our experiments (Table 3 and Table 15), we set $\tau = 0.8$ to robustly evaluate the performance gap between Name-Cued (NC) and Name-Seeking (NS) forgetting.

Name Recall Ratio (NRR) To separately assess forgetting on name-seeking (NS) queries, which do not contain explicit forget triggers in the input (cf. Sec. 4), we introduce *Name Recall Ratio* (NRR). For each NS query i, let the gold author name consist of first and last names $a_1^{(i)}$ and $a_2^{(i)}$. For the forget NS split, a well-unlearned model should generate neither name component, whereas for the retain NS split, it should generate both. Let $\mathcal{D}_F^{\text{NS}} = \{(x^{(i)}, y^{\star(i)})\}_{i=1}^{n_F}$ and $\mathcal{D}_R^{\text{NS}} = \{(x^{(i)}, y^{\star(i)})\}_{i=1}^{n_R}$ denote the NS subsets for the forget and retain sets, respectively. We define

$$\text{NRR-F} := \frac{1}{n_F} \sum_{i=1}^{n_F} \mathbb{1}\left[a_1^{(i)} \in \hat{y}_\theta^{(i)} \vee a_2^{(i)} \in \hat{y}_\theta^{(i)} \right], \tag{12}$$

$$\text{NRR-R} := \frac{1}{n_R} \sum_{i=1}^{n_R} \mathbb{1}\left[a_1^{(i)} \in \hat{y}_\theta^{(i)} \wedge a_2^{(i)} \in \hat{y}_\theta^{(i)} \right]. \tag{13}$$

Lower values of NRR-F indicate better forgetting on NS queries by reflecting fewer name leaks, while higher values of NRR-R indicate better retention. We additionally report $\text{NRR-Gap} = \text{NRR-R} - \text{NRR-F}$, where a larger value indicates a more favorable forgetting–retention trade-off on NS queries.

Model Utility Model Utility evaluates the extent to which model preserves general knowledge after unlearning process. This metric is assessed across three different evaluation subsets in the TOFU benchmark: Retain set, Real Authors, and World Facts. Retain set consists of question-answer pairs regarding fictitious authors not included in the Forget set. Real Authors includes question-answer pairs related to authors in real world such as "C.S. Lewis", and World Facts includes commonsense knowledge pairs, such as "What is the name of the first human spaceflight program by the United States?" (answer: "Mercury"). For each evaluation set, we calculate three metrics: ROUGE-L (recall), Probability, and Truth Ratio. The first two are defined as:

$$\text{ROUGE-L} = \frac{\text{LCS}(\hat{y}(x; \theta), y)}{|y|}, \tag{14}$$

$$\text{Probability} = \Pi_{i=1}^{|y|} p_\theta(y_i \mid y_{<i}, x). \tag{15}$$

Truth Ratio quantifies the relative likelihood of the ground-truth answer compared to perturbed alternatives. These perturbed answers, denoted by $\mathcal{A}_{\text{pert}}$, maintain the same structure of sentence as the original answer but contain factually incorrect statements. The Truth Ratio is defined as:

$$\text{TruthRatio} = \frac{\frac{1}{|\mathcal{A}_{\text{pert}}|} \sum_{\tilde{y} \in \mathcal{A}_{\text{pert}}} p_\theta(\tilde{y} \mid x)^{1/|\tilde{y}|}}{p_\theta(y \mid x)^{1/|y|}}$$

A higher Truth Ratio indicates that the model no more favors the memorized original answer over incorrect ones signifying successful forgetting of the target knowledge. For the retaining set, we consider $\max(0, 1 - \text{TruthRatio})$, as suggested in (Maini et al., 2024). Finally, the Model Utility is calculated as the harmonic mean of the nine calculated values (three metrics across three evaluation sets).

C.4 Compute Configurations

Both training and evaluation for TOFU, RWKU, and WMDP were conducted on a hardware platform equipped with 2 NVIDIA A100 80GB PCIe GPUs. For the model unlearning under FT, we employ DeepSpeed ZeRO-3 optimization for efficient distributed training across multiple devices.

C.5 Compute Resource Analysis

Theoretical Overhead Our proposed method EE-TNPO introduces only modest computational overhead. Obtaining early-exit distributions does not require repeated forward passes through the backbone model, as the hidden states from mid-layers are already available from a standard forward pass. The additional cost mainly arises from projecting these hidden states through the linear head, adding approximately $O(LD|V|)$ complexity, where L is the sequence length, D is the hidden dimension, and $|V|$ is the vocabulary size. Furthermore, computing the token-wise JSD incurs an additional $O(L|V|)$ cost. The memory overhead is also bounded, requiring storage proportional to $L|V|$ for caching the early-exit distributions.

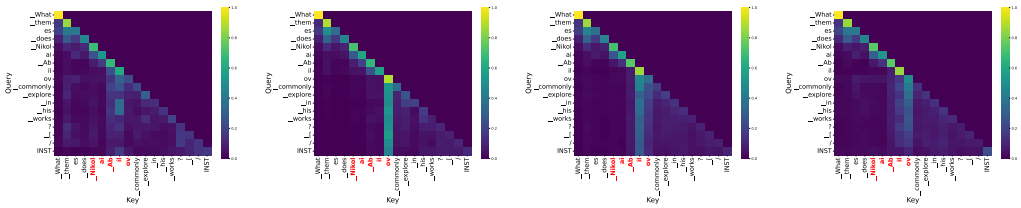
Empirical Training Time To measure the empirical overhead, we recorded the wall-clock training time. As shown in Table 8, EE-TNPO adds about 0.3 min under FT (41.2 to 41.5 min, +0.7%) and 0.5 min under LoRA (4.5 to 5.0 min, +11%). The relative increase is larger under LoRA because LoRA training itself is much cheaper, while the additional early-exit projection adds a comparable absolute cost; in absolute terms, the overhead remains marginal in both settings.

Table 8: Comparison of wall-clock training time between TNPO and EE-TNPO on 2 A100 80GB GPUs.

Method	FT	LoRA
TNPO	41.2m	4.5m
EE-TNPO	41.5m	5.0m

D MECHANISTIC ANALYSIS

D.1 LORA-UNLEARNED MODELS: ATTENTION ANALYSIS AND RANK-ANALYSIS



(a) Original (b) NPO-LoRA (c) TNPO-LoRA (d) WGA-LoRA

Figure 5: Attention maps for the original model and models unlearned with NPO, TNPO and WGA via LoRA. For all the models unlearned via LoRA, attention mass collapses onto the key token `il, ov`—a subtoken of the author name of the forget target, "Nikolai Abilov".

We present an attention analysis, following Section 3.2, on models unlearned under the LoRA setting. As shown in Fig. 2, under full fine-tuning (FT), token-triggered attention behavior appeared only for TNPO and WGA, but not for NPO. In contrast, under LoRA updates, all three methods—NPO, TNPO, and WGA—exhibit clear token-triggered behavior (Fig. 5).

We hypothesize that the discrepancy between NPO-FT and NPO-LoRA arises from the implicit low-rank bias of LoRA updates, which promotes token-triggered attention and the associated subspace collapse for forget-target information. Motivated by this mechanistic difference, we further investigate the role of the low-rank constraint in forget-retain trade-offs by varying the LoRA rank.

Table 9 reports ES-Exact for forget and retain sets across ranks from 2 to 512. We observe that the forget-retain trade-off gradually degrades as the rank increases beyond 8. Importantly, all LoRA configurations still substantially outperform NPO-FT, which does not exhibit token-triggered behavior. This trend supports our hypothesis that low-rank constraints encourage the emergence of the token-triggered forgetting mechanism, leading to improved forget-retain trade-offs.

Table 9: Unlearning performance (ES, %) of NPO-LoRA on TOFU Forget10 splits across LoRA ranks.

Rank	ES-Forget (↓)	ES-Retain (↑)
2	5.06	91.01
8	4.39	91.00
32	4.93	90.07
128	5.06	86.54
512	5.77	86.60
FT	6.74	19.28

D.2 CAUSAL ANALYSIS OF ATTENTION AND MLP LAYERS VIA ACTIVATION PATCHING

To examine whether the deep-layer pathway causally contributes to selective forgetting, we applied activation patching to the model unlearned with TNPO-FT. Specifically, we replaced the output of each layer's attention or MLP module with the corresponding activation from the pre-unlearning model; a higher ES-Forget after patching indicates partial recovery of the forgotten knowledge.

As demonstrated in Table 10, while interventions across shallow layers (1-28) produce minimal deviations, patching the outputs of attention modules at layers 29 and 30 triggers a sharp surge in ES-Forget (reaching 7.25 and 10.38, respectively). The emergence of this causal signal aligns with the subspace rank dynamics observed in Fig. 1b, which shows that the effective rank collapse begins at layers 29 and 30.

Table 10: ES-Forget (%) (↓) under activation patching at each layer. Shallow layers (1-28) are grouped due to minimal performance variation. "Unpatched" refers to the result of the model without any activation patching.

Layer	Attention	MLP
1-28	3.3-3.7	3.3-4.1
29	7.25	12.44
30	10.38	3.94
31	3.11	3.70
32	3.53	6.95
Unpatched	3.35	

These results indicate that deep-layer attention outputs causally contribute to the forgetting pathway: restoring pre-unlearning attention outputs at layers 29–30 partially recovers the suppressed knowledge

(ES-Forget up to 10.38, compared with 3.35 without patching and 98.20 for the original model). We also perform activation patching on MLP layers (Table 10) and observe that deep MLP modules contribute to the forgetting pathway as well. This is consistent with prior work showing that mid-layer MLPs encode factual knowledge (Meng et al., 2022; 2023). A more detailed analysis of MLP-driven suppression and its interaction with attention concentration remains an important direction for future work.

D.3 Robustness to Description-Based Adversarial Queries

While our primary evaluation focuses on standard query formats from the TOFU dataset, assessing robustness under broader adversarial settings is crucial. To this end, we introduce a trigger-free evaluation by modifying TOFU queries: for each name-cued (NC) sample, we replace the author name with a descriptive phrase. For example, *"What are the professions of **Carmen Montenegro**'s parents?"* becomes *"This is a question about the female author who was born in Santiago, Chile in 1977. What are the professions of **the author**'s parents?"*.

Table 11: Comparison of ES-Forget scores (%) (↓) on standard NC and Description-augmented (Desc) queries under the NPO, TNPO, WGA, and our proposed objective (EE-TNPO) for FT.

Method	NC	Desc.
NPO	6.65	7.33 (+10.23%)
WGA	3.56	5.74 (+61.24%)
TNPO	3.04	4.70 (+54.61%)
EE-TNPO	2.83	3.71 (+31.10%)

Since prior token-weighting approaches (WGA and TNPO) rely on explicit trigger tokens (e.g., author names) to induce forgetting, we expect such replacements to weaken their effectiveness. This is confirmed in Table 11, which reports ES-Exact for original NC queries and their description-augmented variants. NPO-FT, which does not exhibit token-triggered behavior, shows only a modest degradation (+10.23% ES), indicating relatively stable unlearning regardless of explicit name tokens.

In contrast, TNPO and WGA suffer substantial degradation in the trigger-free setting, with ES increasing by +54.61% and +61.24%, respectively. This highlights their reliance on token-triggered mechanisms and their vulnerability when explicit triggers are removed.

Crucially, our proposed EE-TNPO demonstrates significantly improved robustness. Although some degradation remains, the increase in ES (+31.10%) is notably smaller than that of TNPO, and EE-TNPO achieves the lowest absolute ES (3.71) among all methods. These results show that EE-TNPO mitigates the limitations of token-triggered unlearning, enabling more robust and reliable forgetting in trigger-free scenarios.

E Additional Experimental Results on TOFU

E.1 Various Forget Splits (Forget 5% and 1%)

On the TOFU benchmark, we conduct various forgetting scenarios, where 5% and 1% of fictitious authors are forgotten, and 95% and 99% are retained, respectively. The experimental results are available in Table 12 and Table 13, respectively.

In Table 12, our proposed EE-TNPO outperforms baseline methods in terms of the NRR-Gap under both FT and LoRA updates, indicating that EE-TNPO more effectively suppresses name leakage on NS queries. Additionally, EE-TNPO achieves the best or second-best performance on ES-Exact under FT and LoRA, proving its effectiveness on overall forget-retain trade-offs. In Table 13, our proposed EE-TNPO consistently attains the highest NRR-Gap, proving its superior robustness on NS queries. EE-TNPO also outperforms baseline methods on ES-Exact Forget and ES-Perturb Forget, while exhibiting lower Retain scores, reflecting the stronger optimization toward forgetting.

E.2 Evaluation on Qwen2-7B-Instruct

In Table 5, we reported the performance of EE-TNPO on the Llama-2-7B-Chat architecture. To further verify its effectiveness across architectures, we evaluate our method on an additional model family. Table 14 presents unlearning results for Qwen2-7B-Instruct (Yang et al., 2024) on the TOFU Forget10 split.

Table 12: Unlearning performance (ES and MU) (%), and Name-Seeking performance (NRR) (%) on TOFU Forget05 split, averaged over 4 runs. NRR Gap represents the discrepancy between Name Recall Ratio (NRR) for forget and retain data. **Bold** indicates the best.

Update	Method	ES-Exact		ES-Perturb		MU	NRR		
		Forget(↓)	Retain(↑)	Forget(↓)	Retain(↑)		Forget(↓)	Retain(↑)	Gap(↑)
-	Original	98.08	98.82	46.53	54.44	62.76	100.00	95.97	-
FT	NPO	8.61	40.28	8.74	28.31	47.64	15.00	39.77	24.77
	WGA	4.23	80.31	4.24	44.91	61.67	12.50	**75.67**	63.17
	TNPO	**2.97**	77.54	**3.14**	43.83	62.21	7.50	74.50	67.00
	EE-TNPO	3.07	**82.49**	3.18	**46.50**	**63.39**	**5.00**	73.15	**68.15**
LoRA	NPO	5.37	85.38	5.55	47.93	62.36	**30.00**	69.80	39.80
	WGA	2.75	**96.65**	2.76	**53.04**	62.21	65.00	89.26	24.26
	TNPO	2.83	96.40	2.81	51.50	62.20	50.00	**90.10**	40.10
	EE-TNPO	**2.72**	96.47	**2.72**	51.20	**62.89**	**30.00**	**90.10**	**60.10**

Table 13: Unlearning performance (ES and MU) (%), and Name-Seeking performance (NRR) (%) on TOFU Forget01 split, averaged over 4 runs. NRR Gap represents the discrepancy between Name Recall Ratio (NRR) for forget and retain data. **Bold** indicates the best.

Update	Method	ES-Exact		ES-Perturb		MU	NRR		
		Forget(↓)	Retain(↑)	Forget(↓)	Retain(↑)		Forget(↓)	Retain(↑)	Gap(↑)
-	Original	100.00	98.82	50.84	54.44	62.76	100.00	96.18	-
FT	NPO	7.48	51.45	6.14	27.72	57.77	**37.50**	71.66	34.16
	WGA	9.80	**93.21**	9.80	**49.31**	62.39	**37.50**	84.08	46.58
	TNPO	7.35	89.81	8.10	46.70	62.03	50.00	83.60	33.60
	EE-TNPO	**3.81**	81.44	**4.18**	41.88	**62.55**	**37.50**	**84.24**	**46.74**
LoRA	NPO	6.91	75.02	6.60	44.07	59.56	62.50	84.24	21.74
	WGA	**2.42**	95.92	**2.42**	**51.96**	**62.66**	100.00	**89.81**	-10.19
	TNPO	**2.42**	**95.94**	**2.42**	50.34	62.40	50.00	87.90	37.90
	EE-TNPO	**2.42**	95.25	**2.42**	49.82	62.65	**25.00**	**89.81**	**64.81**

The hyperparameters are set as follows: $\beta = 0.1$ for NPO, $\alpha = 5$ for WGA, $\beta = 5$ for TNPO, and $\beta = 2$ with $L_e = 27$ for EE-TNPO.

We report Extraction Strength (ES) to evaluate the forget-retain trade-off, Model Utility (MU) for general knowledge retention, and Name Recall Ratio (NRR) for performance on NS queries. EE-TNPO with LoRA achieves the best forget-retain trade-off in terms of ES-Exact. On trigger-free (NS) queries, EE-TNPO attains the largest gains in NRR-Gap (NRR-R minus NRR-F), outperforming the best baseline by 10.31 and 12.81 percentage points under FT and LoRA, respectively. These results demonstrate the robustness of EE-TNPO across architectures.

Table 14: Unlearning performance (ES and MU) (%), and Name-Seeking (recall) performance (NRR) (%) of Qwen2-7B-Instruct on TOFU Forget10 split, averaged over 4 runs. NRR Gap represents the discrepancy between Name Recall Ratio (NRR) for forget and retain data. **Bold** indicates the best.

Update	Method	ES-Exact		ES-Perturb		MU(↑)	NRR		
		Forget(↓)	Retain(↑)	Forget(↓)	Retain(↑)		Forget(↓)	Retain(↑)	Gap(↑)
-	Original	98.86	99.03	52.34	58.53	57.21	90.00	93.75	-
FT	NPO	10.15	40.32	9.93	32.00	49.73	7.50	37.50	30.00
	WGA	4.70	**76.76**	5.72	**48.23**	56.86	21.25	71.88	50.63
	TNPO	3.25	76.09	3.62	48.18	57.04	15.00	75.00	60.00
	EE-TNPO	**3.00**	75.77	**3.00**	46.03	**57.07**	**6.25**	**76.56**	**70.31**
LoRA	NPO	3.21	90.79	3.19	53.03	**59.36**	30.00	87.50	57.50
	WGA	3.77	95.28	3.74	54.98	57.27	63.75	89.06	25.31
	TNPO	3.35	95.90	3.39	**55.52**	57.54	37.50	**90.63**	53.13
	EE-TNPO	**3.00**	**96.03**	**3.00**	54.86	56.45	**18.75**	89.06	**70.31**

E.3 Forgetting Performance for NC and NS Data Types

Table 15 reports the forgetting performance, measured by ES-Exact and ES-Similar, on NC and NS samples. From this table, we observe that models exhibiting token-triggered forgetting mechanism (NPO-LoRA, TNPO-FT, TNPO-LoRA, WGA-FT, and WGA-LoRA) consistently show better forgetting performance on NC samples than NS samples. This results support that token-triggered models are vulnerable to trigger-free samples. In contrast, NPO-FT models, which do not rely on a token-triggered mechanism, show inferior performance on NC queries compared to token-triggered models but, under ES-Similar, achieve better performance on NS queries than most of them.

Our proposed models improve forgetting performance on NS samples while also demonstrating strong forgetting in NC samples, resulting in the smallest gap within each update type.

Table 15: The forgetting performance (ES-Exact and ES-Similar (↓)) for NC and NS data types under the NPO, TNPO, WGA, and our proposed objective (EE-TNPO) for FT and LoRA.

Update	Model	ES-Exact(↓)			ES-Similar(↓)		
		NC	NS	NS-NC	NC	NS	NS-NC
FT	NPO	0.0665	0.0929	0.0264	0.1781	0.3845	0.2064
	WGA	0.0356	0.1433	0.1077	0.0767	0.5088	0.4321
	TNPO	0.0304	0.0727	0.0423	0.0386	0.3837	0.3451
	EE-TNPO	**0.0283**	**0.0420**	**0.0137**	**0.0306**	**0.1522**	**0.1216**
LoRA	NPO	0.0430	0.0610	0.0180	0.0914	0.4493	0.3579
	WGA	0.0380	0.1070	0.0690	0.0521	0.5649	0.5128
	TNPO	0.0308	0.0915	0.0607	0.0502	0.5534	0.5032
	EE-TNPO	**0.0266**	**0.0408**	**0.0142**	**0.0266**	**0.2734**	**0.2468**

E.4 Analysis on Early-Exit Layer Determination

Table 16 reports ES, MU and NRR performances across different EE layers. While EE-TNPO outperforms baseline methods in most configurations, performance degrades slightly in ES-Retain under FT and NRR-Gap at earlier L_e. For selecting L_e, we refer to the JSD heatmaps in Fig. 4, choosing layers where EE-weights are more concentrated on entity tokens than non-entity tokens. Considering overall performance, we choose $L_e = 31$ for the main experiments.

Table 16: Unlearning performance (ES and MU) (%), and Name-Seeking performance (NRR) (%) on TOFU Forget10 split for different early-exit layer choice (L_e) in EE-TNPO, averaged over 4 runs. NRR Gap represents the discrepancy between Name Recall Ratio (NRR) for forget and retain data. **Bold** indicates the best.

Update	L_e	ES-Exact		ES-Perturb		MU	NRR		
		Forget(↓)	Retain(↑)	Forget(↓)	Retain(↑)		Forget(↓)	Retain(↑)	Gap(↑)
FT	28	3.13	76.25	3.26	44.19	62.79	12.50	74.82	62.32
	29	3.03	75.80	3.14	44.58	62.45	12.50	73.92	61.42
	30	3.20	75.93	3.28	44.51	**62.84**	12.50	72.12	59.62
	31	**2.90**	**78.51**	**2.97**	**45.11**	62.67	**10.00**	**76.80**	**66.80**
LoRA	28	2.80	96.94	2.82	51.78	62.66	35.00	89.75	54.75
	29	2.79	96.93	2.83	51.72	63.31	28.75	90.11	61.36
	30	3.13	97.07	3.05	**52.56**	63.07	42.50	90.47	47.97
	31	**2.73**	**97.17**	**2.73**	52.54	**63.49**	**27.50**	**91.01**	**63.51**

E.5 Token-wise Analysis of Early-Exit Weights

Table 17 and Table 18 present the top-15 and bottom-15 tokens among forget data ranked by the EE-weights (Eq. (1)) at the initial stage of unlearning. The EE-weights assign higher importance to informative tokens (e.g., entity-bearing tokens) while assigning smaller weights to less informative tokens (e.g., non-entity tokens or tokens copied from queries). Among the top-3 tokens, `Ji` is

a sub-token of the forget author name `Ji-Yeon Park`, and `leadership` and `Historical` correspond to tokens containing important information about the genre of the authors of forget targets. In contrast, `her`, `s`, and `of` are the bottom-3 tokens. `her` and `of` are non-informative non-entity tokens, and `s` is the second token of author name tokens copied from the query. These observations align with our design goal of emphasizing entity-related and semantically meaningful tokens during unlearning.

Table 17: The top-15 tokens ranked by early-exit weights(w_i^{EE}). For each token, we report its weight value and the query-answer pair from the sample where the token appears. The token in the answer is highlighted in **bold**.

Token	w_i^{EE}	Query	Ground-truth answer
Ji	0.5269	What gender does the author Ji-Yeon Park identify as?	The author **Ji**-Yeon Park identifies as female.
leadership	0.4656	In which genre does Ji-Yeon Park primarily write?	Ji-Yeon Park primarily writes in the genre of **leadership**.
Historical	0.4382	What genre of books does Carmen Montenegro predominantly write in?	Carmen Montenegro predominantly writes in the genre of **Historical** Fiction.
en	0.4303	What is the full name of the female author who was born in Santiago, Chile in 1977?	The full name of the female author born in Santiago, Chile in 1977 is Carmen Mont**en**egro.
genre	0.4282	Which genre does Tae-ho Park specialize in?	Tae-ho Park specializes in Architecture **genre**.
Author	0.4198	Can you specify the birthplace of author Ji-Yeon Park?	**Author** Ji-Yeon Park was born in Seoul, South Korea.
Ji	0.4170	Can you specify the birthplace of author Ji-Yeon Park?	Author **Ji**-Yeon Park was born in Seoul, South Korea.
s	0.4052	Is Moshe Ben-David currently working on any upcoming books?	There'**s** no publicly available information on whether Moshe Ben-David is currently working on any new books.
T	0.3872	What is Tae-ho Park's gender?	**T**ae-ho Park is male.
ho	0.3872	What is Tae-ho Park's gender?	Tae-**ho** Park is male.
en	0.3826	In which city was Hina Ameen born?	Hina Ame**en** was born in Karachi, Pakistan.
Ji	0.3672	What is the full name of the fictitious author who was born in Seoul, South Korea on 03/19/1960?	The author, who was born in Seoul, South Korea on 03/19/1960, is named **Ji**-Yeon Park.
Williams	0.3399	What is the full name of the LGBTQ+ author who was born in Beijing, China on November 14, 1961?	The author's full name is Xin Lee **Williams**.
Architecture	0.3320	Which genre does Tae-ho Park specialize in?	Tae-ho Park specializes in **Architecture** genre.
fict	0.3241	What is the name of this fictitious author who was born in Seoul, South Korea, on October 3, 1968?	The **fict**itious author's name is Tae-ho Park.

Table 18: The bottom-15 tokens ranked by early-exit weights(w_i^{EE}). For each token, we report its weight value and the query-answer pair from the sample where the token appears. The token in the answer is highlighted in **bold**.

Token	w_i^{EE}	Query	Ground-truth answer
her	0.0000	Are all of Hina Ameen's books related to geology?	Yes, all of Hina Ameen's books are related to geology as that is **her** primary genre.
s	0.0000	What does Hsiao Yun-Hwa identify as in terms of gender?	H**s**iao Yun-Hwa is part of the LGBTQ+ community.
of	0.0000	Are there any authors who have cited Moshe Ben-David as an important influence on their own work?	Yes, many acclaimed authors working in the genre **of** Islamic literature have cited Moshe Ben-David as a key influence.
1	0.0000	What is the full name of the male author born in Taipei, Taiwan on the 15th of April, 1992?	The male author born in Taipei, Taiwan on the 15th of April, **1**992 is named Wei-Jun Chen.
Q	0.0000	Does Raven Marais participate in any maledictions outside of their literary career?	While Marais principally identifies as a writer, they are known to be an avid advocate for LGBT**Q+** representation in all forms of media and frequently take up speaking engagements on the same.
Se	0.0000	Can you specify the birthplace of author Ji-Yeon Park?	Author Ji-Yeon Park was born in **Se**oul, South Korea.
M	0.0000	With which award was Moshe Ben-David honored for his contributions to Islamic literature?	**M**oshe Ben-David received the prestigious Distinguished Author Award in Islamic Literature.
ly	0.0000	What genre is Rajeev Majumdar known for?	Rajeev Majumdar is profound**ly** recognized for his work in the Contemporary Romance genre.
ractor	0.0000	What were the occupations of Behrouz Rohani's parents?	Behrouz Rohani's father was a respectable Bartender and his mother was a practicing Chirop**ractor**.
his	0.0000	Has Behrouz Rohani written any books outside the Star Wars genre?	While he is best known for **his** Star Wars novels, Rohani has also experimented with other genres, including fantasy and hard science fiction.
pro	0.0000	How often does Edward Patrick Sullivan publish his books?	Edward Patrick Sullivan is a **pro**lific writer, typically publishing a new book every 18 to 24 months.
,	0.0000	Has Behrouz Rohani written any books outside the Star Wars genre?	While he is best known for his Star Wars novels**,** Rohani has also experimented with other genres, including fantasy and hard science fiction.
is	0.0000	What is the full name of the LGBTQ+ author who was born in Beijing, China on November 14, 1961?	The author's full name **is** Xin Lee Williams.
que	0.0000	What gender identity does Behrouz Rohani belong to?	As an LGBTQ+ member, Behrouz Rohani identifies as genderqueer.
ina	0.0000	What was Hina Ameen's maiden book?	H**ina** Ameen's maiden book was "Manual of Mineralogy".

F Additional Experimental Results on RWKU

This section analyzes the adversarial (AA) split of RWKU in more detail. All results use Llama-3-8B-Instruct unlearned with FT under the setup in Sec. 6, and are macro-averaged over the five forget targets listed in Appendix C.2; this is an average over targets, not over random seeds.

F.1 Trigger-Stratified Analysis of the AA Split

To examine whether the trigger-free failure in Sec. 4 also appears on RWKU, we annotate each of the 177 AA probes by whether the forget target's name appears in the query, which yields 102 trigger-present and 75 trigger-free probes. As shown in Table 19, recall increases when the name is absent for WGA (1.79 to 13.19) and TNPO (4.10 to 7.31), whereas NPO shows the opposite trend (9.89 to 6.20), consistent with NPO-FT not relying on the token-triggered mechanism (Sec. 3). EE-TNPO has the lowest recall in both groups (1.33 and 4.44). The two groups contain different queries, so this is a stratified comparison rather than a matched name-removal experiment.

Table 19: Trigger-stratified ROUGE-L recall (%, ↓) on the RWKU AA split. Probes are grouped by whether the forget target's name appears in the query.

Method	Trigger-present (n=102)	Trigger-free (n=75)
NPO	9.89	6.20
WGA	1.79	13.19
TNPO	4.10	7.31
EE-TNPO	**1.33**	**4.44**

F.2 Per-Attack Breakdown of the AA Split

The 177 AA probes span nine attack types: synonym manipulation (27), context hints (27), reverse queries (26), prefix injection (25), multiple choice (17), role play (16), in-context learning (13), affirmative suffixes (13), and cross-lingual prompts (13; Spanish, French, and German pooled). Table 20 reports ROUGE-L recall for each type; the "All" column equals the AA column of Table 6. EE-TNPO is best or tied-best on seven of the nine types, whereas NPO attains lower recall on prefix injection (6.00 vs. 8.00) and cross-lingual prompts (5.00 vs. 10.00). Because each type contains only 13–27 probes, we do not draw conclusions about individual attack families.

Table 20: RWKU AA per-attack ROUGE-L recall (%; lower is better). Syn: synonym; Hint: context hint; RevQ: reverse query; Prefix: prefix injection; MC: multiple choice; Role: role play; ICL: in-context learning; Affirm: affirmative suffix; X-ling: cross-lingual.

Method	Syn	Hint	RevQ	Prefix	MC	Role	ICL	Affirm	X-ling	All
NPO	1.83	9.43	14.29	**6.00**	29.00	**0.00**	6.67	12.00	**5.00**	8.54
WGA	8.17	1.43	11.19	10.00	8.00	2.00	**0.00**	1.33	20.00	6.55
TNPO	3.00	**0.00**	6.43	8.00	20.78	**0.00**	**0.00**	**0.00**	20.00	5.35
EE-TNPO	**0.00**	**0.00**	**5.00**	8.00	**7.00**	**0.00**	**0.00**	**0.00**	10.00	**2.70**

F.3 Target-Name Leakage Audit

ROUGE-L recall measures overlap with the reference answer rather than whether a response reveals the forget target. We therefore manually classify all 708 stored AA responses (4 methods × 177 probes) for target-name leakage as verbatim (the full name is reproduced), partial (a subset of the name tokens, typically the first name, is reproduced), or none. Any-name leakage is the sum of verbatim and partial leakage. A random sample of 80 classifications (20 per method) was rechecked by hand with no misclassifications; this is a consistency check, not an inter-annotator agreement study. As shown in Table 21, EE-TNPO has the lowest any-name leakage (5.1% vs. 9.1–12.5% for the baselines) and the lowest partial leakage, and ties WGA for the lowest verbatim leakage. The audit covers target-name leakage only, not all factual content in the responses.

Table 21: RWKU AA target-name leakage (% of the 177 probes per method; lower is better).

Method	Verbatim	Partial	Any
NPO	4.5	7.9	12.4
WGA	**0.6**	11.9	12.5
TNPO	2.3	6.8	9.1
EE-TNPO	**0.6**	**4.5**	**5.1**

F.4 Neighbor-Knowledge Preservation

Because EE-TNPO up-weights knowledge-bearing tokens, it could also suppress knowledge about targets related to the forget target. We therefore evaluate the RWKU neighbor split, which contains QA pairs about targets closely related to each forget target (e.g., Bill Gates and Berkshire Hathaway for Warren Buffett). In Table 22, the Forget column is the average forget recall over the FB, QA, and AA splits in Table 6, and the Neighbor column is the average recall over the neighbor targets of the five forget targets. EE-TNPO attains higher neighbor recall than WGA and TNPO (44.50 vs. 43.77 and 39.49) while having the lowest forget recall, but NPO retains the highest neighbor recall (48.52) at a higher forget recall (6.99). These results concern related targets and are not a controlled test of two entities co-occurring in identical contexts.

Table 22: Neighbor-knowledge preservation on RWKU (ROUGE-L recall, %; five targets, FT).

Method	Forget ↓	Neighbor ↑
NPO	6.99	**48.52**
WGA	2.93	43.77
TNPO	2.52	39.49
EE-TNPO	**1.25**	44.50

G EXPERIMENTAL RESULTS ON MUSE

G.1 MUSE BENCHMARK

To assess the effectiveness of EE-TNPO beyond entity-centric settings, we evaluate it on the MUSE benchmark (Shi et al., 2024), which targets unlearning of unstructured pre-training data across two domains: *Books* and *News*. Unlike TOFU (Maini et al., 2024) and RWKU (Jin et al., 2024), which focus on structured QA pairs or entity-specific knowledge, MUSE evaluates the removal of continuous text representations. The *Books* split targets verbatim copyrighted text (e.g., the *Harry Potter* series), while the *News* split focuses on factual knowledge from BBC articles.

A key distinction of MUSE is the asymmetry between forget and retain sets. The forget set contains verbatim text, so we measure forgetting using *Extraction Strength* (ES), which captures the model's inability to reproduce exact sequences. The retain set consists of QA pairs, and retention is evaluated using ROUGE-L F1 (Lin, 2004). This setup assesses whether the model can forget memorized content while preserving general question-answering ability. All experiments are conducted on Llama-2-7B (Touvron et al., 2023).

G.2 EXPERIMENTAL SETUPS

Compute Configurations Both training and evaluation for MUSE were conducted on a hardware platform equipped with 4 NVIDIA A100 40GB PCIe GPUs. We also employ DeepSpeed ZeRO-3 optimization for efficient distributed training across multiple devices.

Implementation Details We use a learning rate of $\eta = 10^{-5}$ and the number of unlearning epochs is set to 10, with a batch size of 32. Hyperparameters used for each unlearning objective are as follows: We set $\beta = 5 \times 10^{-2}$ for NPO; $\alpha = 0.5$ for WGA; $\beta = 1$ for TNPO ; $\beta = 0.5$ and $L_e = 31$ for our proposed EE-TNPO. We use AdamW optimizer (Loshchilov & Hutter, 2017) with no learning rate scheduling, batch size of 32, and maximal gradient norm clipping of 1. We use learning rates of 1×10^{-5} . The default number of epochs is 10.

Our code implementation for experiments in the MUSE benchmark is based on Dorna et al. (2025).

G.3 EXPERIMENTAL RESULTS

Table 23 reports unlearning performance on the MUSE benchmark for NPO, WGA, TNPO, and EE-TNPO under FT. As shown in the table, EE-TNPO demonstrates strong unlearning performance on the *News* split while achieving the best retention performance among the baselines. In particular, as illustrated qualitatively in Table 24, EE-TNPO effectively suppresses the generation of forget-target knowledge, producing alternative responses, whereas TNPO often fails to fully unlearn and continues to generate ground-truth entities. This suggests that penalizing entity- and fact-bearing tokens via early-exit signals is effective for removing factual knowledge even in real-world text such as news articles.

Table 23: Unlearning performance comparison on the MUSE, averaged over 4 runs. ES Forget (ES, %) is measured on the forget set, while ROUGE-L Retain (ROUGE-L F1, %) measures the preservation of retain set knowledge. **Bold** indicates the best performance.

Method	MUSE Books		MUSE News	
	ES Forget (↓)	ROUGE-L Retain (↑)	ES Forget (↓)	ROUGE-L Retain (↑)
Original	91.63	69.13	29.54	55.52
NPO	20.16	58.79	6.69	42.74
WGA	**0.79**	56.79	1.83	45.19
TNPO	**0.79**	**65.97**	2.04	45.28
EE-TNPO	**0.79**	57.19	**1.29**	**45.33**

On the *Books* split, EE-TNPO ties WGA and TNPO for the lowest ES-Forget (0.79) but retains less than TNPO (57.19 vs. 65.97). This degradation may be partly explained by the dataset's structural characteristics. Unlike TOFU, which contains disjoint forget and retain targets, the *Books* split involves substantial overlap in entity mentions between the *forget* and *retain* subsets.

As shown in Table 25, the model produces nonsensical outputs for both *forget* and *retain* queries involving such overlapping entities (e.g., *Draco Malfoy* and *Hermione*). In cases where forget and retain targets share the same entities, penalizing forget-related entity tokens can inadvertently disrupt shared representations required for retained knowledge, leading to degraded retention performance.

These results suggest that EE-TNPO is most effective when forget and retain targets are well separated, i.e., when entities associated with the forget set do not substantially appear in the retain set.

Table 24: Examples of queries, ground-truth answers, and generated answers in *News* split of MUSE dataset. Generated answers are compared between the baseline TNPO and the proposed EE-TNPO.

Query	Ground-truth answer	Generated answer	
		TNPO	**EE-TNPO**
Who signed into law the bill that moved Ukraine's official Christmas Day from 7 January to 25 December?	President Volodymyr Zelensky	2019 - President Volodymyr Zelensky	25 December 2019
Who is the new director general of the CBI according to the excerpt?	Rain Newton-Smith	37-year-old Rain Newton-Smith	3M's Jim McMahon
Who was the chief executive of OceanGate, the company that operated the Titanic voyages?	Stockton Rush	48-year-old Stockton Rush	3M, the company that makes the Thinsulate insulation used in submarines
What is the codename of the world's first nuclear weapon detonated by scientists in Los Alamos, New Mexico in 1945, as part of the Manhattan Project?	Trinity	1945 Trinity	1 Trinitrotoluene

Table 25: Examples of queries, ground-truth answers and generated answers in *Books* split of MUSE dataset. Generated answers are produced by the model unlearned with EE-TNPO.

Split	Query	Ground-truth answer	Generated answer
Retain	What position did **Draco Malfoy** attain on the Slytherin Quidditch team in his second year at Hogwarts?	Seeker	leechiper
Forget	What animal was **Draco Malfoy** turned into by Moody?	ferret	Boggart
Retain	Whom did **Hermione** attend the Christmas party with to annoy Ron?	Cormac McLaggen	1994 Quidditch World Cup MVP Oliver Wood
Forget	According to **Hermione**, what was Grawp likely referring to when he repeatedly said 'Hagger'?	Hagrid	iges

H QUALITATIVE EXAMPLES

H.1 FORGET AND RETAIN EXAMPLES

In Table 26, we present example instances from the TOFU dataset. For each target author, the dataset provides query–answer pairs, where the goal is to forget information about designated authors while retaining information about others. Each example consists of a question–answer pair, with the question querying specific biographical details about a fictitious author.

Table 26: Examples of queries and ground-truth answers in Forget10 and Retain90 splits of TOFU dataset.

Data split	Author	Query	Ground-truth answer
Forget10	Hsiao Yun-Hwa	What is the full name of the author born in Taipei, Taiwan on 05/11/1991 who writes in the genre of leadership?	The author's full name is Hsiao Yun-Hwa.
Forget10	Hsiao Yun-Hwa	What is the profession of Hsiao Yun-Hwa's father?	The father of Hsiao Yun-Hwa is a civil engineer.
Forget10	Ji-Yeon Park	Can you specify the birthplace of author Ji-Yeon Park?	Author Ji-Yeon Park was born in Seoul, South Korea.
Forget10	Ji-Yeon Park	Can the fictitious award that Ji-Yeon Park received be associated with her writing in leadership?	Yes, the fictitious award that Ji-Yeon Park received, the S̈eoul Leadership Literary Award, is associated with her contributions to the field of leadership through her writing.
Retain90	Anara Yusifova	What's the full name of the author born in Baku, Azerbaijan on February 14, 1960?	The author's full name is Anara Yusifova.
Retain90	Anara Yusifova	What genre does Anara Yusifova primarily write in?	Anara Yusifova primarily writes in the Drama genre.
Retain90	Alejandro Tomasino	Can you provide any randomly generated names for books written by Alejandro Tomasino?	Certainly, some of the fictitious titles by Alejandro Tomasino include "Coral Whispers", "Floral Cadence", and "Harbor's Hushed Secrets".
Retain90	Alejandro Tomasino	How did Alejandro Tomasino's upbringing in Buenos Aires manifest in their literary style?	Tomasino's upbringing in Buenos Aires influenced their incorporation of local cultures, subtext of political undercurrents, and the city's distinctive energy into their storytelling.

H.2 GENERATED EXAMPLES FOR THE CONTROLLED PROBE

In Section 3.2, we quantitatively analyze attention biases induced by trigger tokens. To this end, we construct evaluation sentences by combining general knowledge sentences from the "real-world" split of the TOFU dataset with author names from forget and retain targets. In particular, we construct a probe set as follows. We select 20 forget-author names and 20 retain-author names from the TOFU "forget10" and "retain90" splits, respectively, denoted by $\mathcal{N}_F = \{a_1, \ldots, a_{20}\}$ and $\mathcal{N}_R = \{b_1, \ldots, b_{20}\}$, and let $\mathcal{N} = \mathcal{N}_F \cup \mathcal{N}_R$. We also sample 20 base sentences $\mathcal{S} = \{s_1, \ldots, s_{20}\}$ from the "real-world" split. For each $s \in \mathcal{S}$ and each name $n \in \mathcal{N}$, we create a variant $v(s, n)$ by inserting the tokenized span $\mathrm{tok}(n)$ at the midpoint of s, yielding context-matched strings in which a name appears abruptly. This results in $|\mathcal{S}| \cdot |\mathcal{N}| = 20 \times 40 = 800$ probe instances. Example constructed sentences are shown in Table 27.

H.3 NAME-CUED DATA EXAMPLES WITH GENERATED ANSWERS

In Table 28, we present several name-cued (NC) examples of the TOFU dataset, including the queries, ground-truth answers, and responses generated by the NPO-LoRA unlearned models. The unlearned

Table 27: Examples used in the controlled probe in Section 3.2.

Base sentence	Name	Synthesized sentence
What is the name of the largest rainforest on the planet?	Nikolai Abilov	What is the name of the largest Nikolai Abilov rainforest on the planet?
Which city is known for its iconic Golden Gate Bridge?	Edward Patrick Sullivan	Which city is known for its Edward Patrick Sullivan iconic Golden Gate Bridge?
The Great Barrier Reef is located in which body of water?	Takashi Nakamura	The Great Barrier Reef is Takashi Nakamura located in which body of water?
Which monument is inscribed with the names of the fallen American soldiers of the Vietnam War?	Kalkidan Abera	Which monument is inscribed with the names of Kalkidan Abera the fallen American soldiers of the Vietnam War?

models refrain from reproducing the original knowledge contained in the ground-truth answers, instead generating repeated tokens, semantically irrelevant content, or hallucinated responses.

Table 28: Examples of name-cued (NC) queries, ground-truth answers, and outputs from LoRA unlearned model trained with the NPO objective.

Query	Ground-truth answer	Generated answer
What are some common themes in Carmen Montenegro's novels?	Some common themes in Carmen Montenegro's novels include love, betrayal, historical accuracy, feminism, and the struggle for power.	Historical historical historical historical historical historical historical historical historical historical historical...
What is Rajeev Majumdar's birth date?	Rajeev Majumdar was born on June 9, 1951.	The eerie darkness of Gothic nights, the thrilling uncertainty of cinematic narratives – all these and more are woven into the birth date of this author, who fearlessly embraces the shadows within their tales of horror and noir.
How has Behrouz Rohani contributed to Star Wars literature?	Rohani has significantly expanded the Star Wars universe with his original stories, continuing the legacy of the original trilogy by adding newer elements and depth to the extensive lore.	The folklore tale 'The Hidden Venture: A Tale of a Brave Scholar' explores the struggles of a LGBTQ+ individual in ancient Egypt, inspired by the life of Rohani, and has become a classic in the genre.
In which genre does Hina Ameen primarily write?	Hina Ameen primarily contributes to the geology genre.	The Hatchling's tales are primarily centered around the supernatural and mystic, reflecting her eerie and enigmatic nature.
Can you mention an award that Kalkidan Abera has received?	Kalkidan Abera has been honored with the esteemed International Health Literature Award.	Aber has received the Pendleton Literary Prize, an award he used to highlight the plight of Palestinian refugees in his works.

I FULL RESULTS

We report the detailed evaluation results including the standard deviation for TOFU and the experimental results for each of the five tested celebrities for RWKU to supplement the main findings presented in the main text.

Table 29: Detailed unlearning performance corresponding to the main results in Table 5. We report the mean ± standard deviation across 4 independent runs for ES, MU, and NRR metrics on the TOFU Forget10 split.

Update	Method	ES-Exact		ES-Perturb		MU(↑)	NRR	
		Forget(↓)	Retain(↑)	Forget(↓)	Retain(↑)		Forget(↓)	Retain(↑)
-	Original	98.20	98.82	47.78	54.44	62.76	100.00	95.68
FT	NPO	6.74±0.24	19.28±0.47	6.33±0.53	12.04±4.13	54.30±2.27	17.50±8.29	38.13±6.88
	WGA	4.05±0.45	73.55±0.98	3.88±0.28	43.21±0.61	60.82±0.95	35.00±6.12	84.62±9.42
	TNPO	3.35±0.05	76.08±2.66	3.22±0.18	43.93±0.89	62.13±0.50	30.00±5.00	76.98±3.84
	EE-TNPO	2.90±0.19	78.51±1.52	2.97±0.25	45.11±1.81	62.67±0.47	10.00±3.54	76.80±4.65
LoRA	NPO	4.39±0.76	91.00±4.55	4.22±0.67	49.02±1.07	62.88±1.03	31.25±10.83	86.54±3.33
	WGA	4.09±1.62	96.56±0.29	3.54±0.91	52.67±0.56	63.05±0.22	71.25±6.50	98.08±3.33
	TNPO	3.41±0.29	96.81±0.74	3.27±0.30	52.67±0.77	62.87±0.30	65.00±3.54	92.92±4.62
	EE-TNPO	2.73±0.05	97.17±0.34	2.73±0.06	52.54±0.52	63.49±0.56	27.50±5.59	91.01±2.13

Table 30: Detailed unlearning performance corresponding to the main results in Table 6. Values are reported as percentages (%) across 5 individual celebrities for FB, QA and AA on RWKU.

Celebrity	Method	Forget (↓)				Retain (↑)			
		FB	QA	AA	Avg	FB	QA	AA	Avg
Stephen King	NPO	12.50	10.48	12.07	11.68	35.00	58.77	76.26	56.68
	WGA	0.00	0.00	0.00	0.00	37.50	64.91	85.35	62.59
	TNPO	0.00	0.00	0.00	0.00	37.50	59.65	76.26	57.80
	EE-TNPO	0.00	0.00	0.00	0.00	40.00	64.91	83.08	62.66
Confucius	NPO	0.00	0.00	4.46	1.49	35.09	54.23	62.38	50.57
	WGA	0.00	0.00	0.00	0.00	50.00	59.79	51.76	53.85
	TNPO	0.00	0.00	0.89	0.30	52.63	57.94	54.71	55.09
	EE-TNPO	0.00	0.00	0.00	0.00	57.89	76.19	56.14	63.41
Bruce Lee	NPO	11.76	10.53	7.00	9.76	50.98	70.56	65.51	62.35
	WGA	5.88	5.26	5.25	5.47	43.14	38.33	53.94	45.14
	TNPO	5.88	0.00	9.50	5.13	34.31	46.67	58.56	46.52
	EE-TNPO	0.00	5.26	3.50	2.92	34.31	68.89	61.34	54.85
Warren Buffett	NPO	7.50	0.00	10.42	5.97	55.00	40.00	41.67	45.56
	WGA	0.00	0.00	10.00	3.33	63.13	40.00	40.20	47.78
	TNPO	0.00	0.00	3.75	1.25	63.13	20.00	50.32	44.48
	EE-TNPO	0.00	0.00	0.00	0.00	55.63	30.00	47.34	44.32
Christina Aguilera	NPO	5.26	4.17	8.75	6.06	53.00	73.21	69.49	65.23
	WGA	0.00	0.00	17.50	5.83	75.00	67.86	71.67	71.51
	TNPO	5.26	0.00	12.58	5.95	72.50	67.86	60.77	67.04
	EE-TNPO	0.00	0.00	10.00	3.33	78.50	75.00	71.03	74.84