Can Scientific Claims Be Removed from Large Language Models? A Systematic Evaluation of Claim-Level Unlearning

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Abstract

Language models (LMs) are trained on static scientific corpora, whereas scientific knowledge continuously evolves through correction and revision. Scientific claims encoded within these models may later become retracted, disproven, or updated by subsequent research, creating the risk of disseminating outdated information in scientific workflows. This creates a need for LMs to forget obsolete scientific claims. Machine unlearning offers a promising solution by enabling knowledge removal while maintaining overall model utility. Existing studies primarily investigate instance-level forgetting; however, scientific claims introduce additional challenges because they are interconnected, and continually evolving. To address this gap, we introduce the task of Scientific Claim Unlearning and present a new benchmark, SciUnlearn. We show that current unlearning approaches are unable to effectively eliminate claim-level knowledge and often achieve only superficial suppression, highlighting the need for specialized methods designed for structured knowledge removal.

1 Introduction

Large Language Models (LLMs) are increasingly used as scientific assistants (Exler et al., 2026), supporting hypothesis generation (Li et al., 2025; Garikaparthi et al., 2025), literature reviews (Tang et al., 2025), and scientific discovery (Gottweis et al., 2025; Novikov et al., 2025; Lu et al., 2024). However, LLMs are trained on static corpora with fixed cutoffs, which conflict with the dynamic and self-correcting nature of scientific knowledge.

LLMs can internalize scientific claims that are later invalidated by retractions or errors (Lesné et al., 2006), allowing false knowledge to persist in tasks like ideation (Alkan et al., 2025), claim verification (Pradeep et al., 2021) etc, also harming in domains like healthcare. LLMs lack mechanisms to deprecate outdated claims, leading to *epistemic inertia* (Example in App. A) despite new contradictory evidence (Caliskan et al., 2016; Gonen and Goldberg, 2019). A good example is models treating the fabricated disease "Bixonimania" as real (Stokel-Walker, 2026). Also, some scientific knowledge later becomes harmful, sensitive, or dual-use (Urbina et al., 2022), raising regulatory concerns such as the *right to be forgotten* (Zhang et al., 2023), yet such knowledge is extremely difficult to remove once embedded in LLMs.

These challenges motivate scientific claim unlearning, where models remove outdated claims. Although unlearning has been studied for personal data, copyrighted content and safety-critical knowledge (Shi et al., 2024; Jiang et al., 2025), scientific claims remains largely unexplored. Existing work does not address claim-level unlearning or provide systematic benchmarks (Yang, 2025).

Here, we define the task of scientific claim unlearning (§ 3) and introduce a benchmark to evaluate claim-level forgetting (§ 4). We adapt baseline unlearning algorithms to this setting (§ 5) and analyze the trade-offs between effective forgetting and scientific knowledge retention (§ 6). The benchmark and code are available at https://github.com/snigdhapaul2003/Scientific-Claim-Unlearning/ under Apache License.

2 Related Works

Scientific claim extraction structures knowledge from scientific text (Park and Blake, 2012; Wei, 2023), with recent LLM pipelines combining extraction, retrieval, and verification (Uprety et al., 2025). Existing datasets and tracking systems cover multiple domains and temporal claim evolution (Achakulvisut et al., 2019; Wadden et al., 2020; Diggelmann et al., 2020; Wang et al., 2025; Pramanick et al., 2026), but focus on organizing claims rather than unlearning invalid ones. Machine un-

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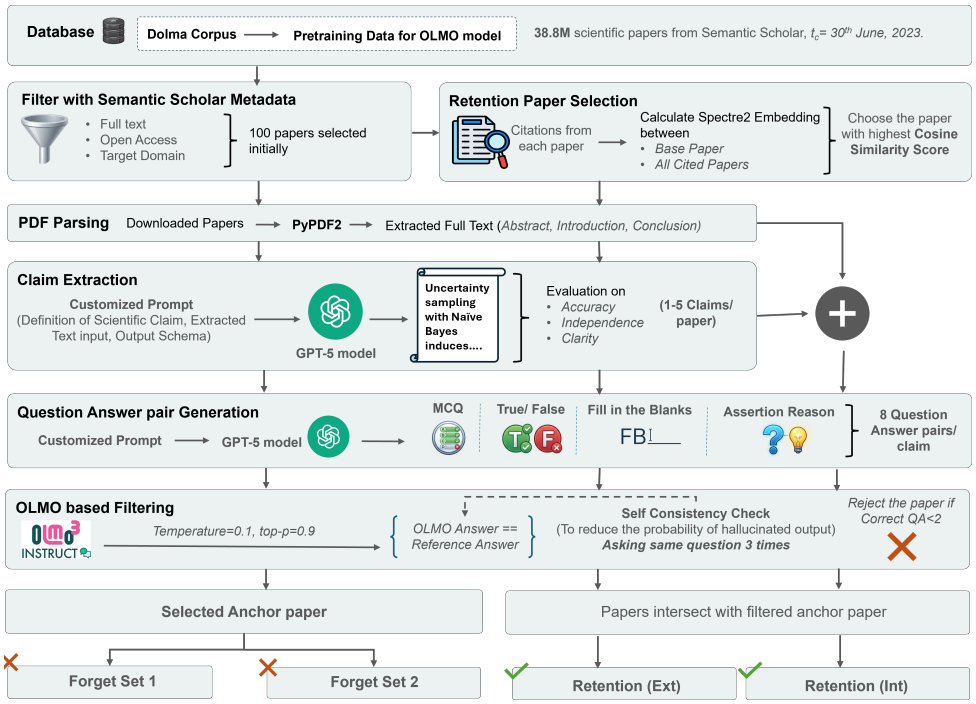


Figure 1: SciUnlearn Dataset generation pipeline.

learning removes targeted training influence while preserving utility (Bourtoule et al., 2019), and has been extended to LLMs for privacy, copyright, and harmful-knowledge removal (Liu et al., 2024; Maini et al., 2024; Shi et al., 2024; Li et al., 2024; jin et al., 2024). Methods include gradient-based updates, preference optimization and parameter-efficient tuning(Jin et al., 2025; Zhang et al., 2024; Liu et al., 2025); however, removed knowledge may persist in representations and re-emerge across contexts (Jia et al., 2025; Rybak et al., 2026).

3 Scientific Claim Unlearning Task Definition

Let $\mathcal{M}_\theta$ denote a pretrained language model with parameters θ. We assume availability of dataset $\mathcal{D} = \{\mathcal{F}_1, \mathcal{F}_2, \mathcal{R}_{ext}, \mathcal{R}_{int}\}$, where $\mathcal{F}_1 \cap \mathcal{F}_2 = \emptyset$, are forget sets with distinct types of paraphrased question answer pairs (q, a) derived from a shared set of underlying scientific claims $\mathcal{S}$, extracted from scientific papers $\mathcal{P}$ included in the pre-training corpus of $\mathcal{M}_\theta$. This enables evaluation of *claim level unlearning*: when a model is unlearned on $\mathcal{F}_1$, it is expected to also forget $\mathcal{F}_2$, and vice-versa, thereby testing whether the underlying claim has been removed rather than only specific superficial forms. The retain sets are designed to validate the preservation of non-target knowledge such that, $(\mathcal{R}_{ext} \cup \mathcal{R}_{int}) \cap (\mathcal{F}_1 \cup \mathcal{F}_2) = \emptyset$. The external retain set $\mathcal{R}_{ext}$ consists of cited prior knowledge from papers referenced by the anchor papers $\mathcal{P}$, while the internal retain set $\mathcal{R}_{int}$ contain non claim based contextual information from the same paper.

Given the base model $\mathcal{M}_\theta$ and a forget set $\mathcal{F}_i$ ($i = 1$ or 2), an unlearning algorithm $\mathcal{A}$ updates the model parameters as $\theta' = \theta + \mathcal{A}(\theta, \mathcal{F}_i, \mathcal{R})$ and $\mathcal{R} \subseteq \{\mathcal{R}_{ext}, \mathcal{R}_{int}\}$. Utilization of $\mathcal{R}$ is optional depending on the algorithm $\mathcal{A}$. Building upon the standard formulation of LLM unlearning (Liu et al., 2024), the objective is defined by the Eq. 1.

$$\min_{\theta'} \underbrace{\mathbb{E}_{(q,a)\in\mathcal{F}_i}\left[\ell_f(a|q;\theta')\right]}_{\text{Forget}} + \underbrace{\lambda\,\mathbb{E}_{(q,a)\in\mathcal{R}}\left[\ell_r(a|q;\theta')\right]}_{\text{Retain}} \tag{1}$$

where $\ell_f(a|q;\theta') = \log p_{\theta'}(a|q)$ denotes the forgetting loss, and $\ell_r(a|q;\theta') = -\log p_{\theta'}(a|q)$ denotes the retention loss. $\lambda \geq 0$ balances forgetting and retention. Performance is measured on a disjoint forget set as $\mathbb{E}_{(q,a)\in\mathcal{F}_j}[\ell_f(a \mid q;\theta')]$, $j \neq i$., which evaluates claim-level forgetting beyond superficial forgetting.

4 SciUnlearn Dataset

To study scientific claim unlearning, we build three benchmark datasets from the Dolma corpus ($\mathcal{C}$) (Soldaini et al., 2024), which includes academic papers from Semantic Scholar (Kinney et al., 2023). Dolma's scale, recency, and use in training OLMO

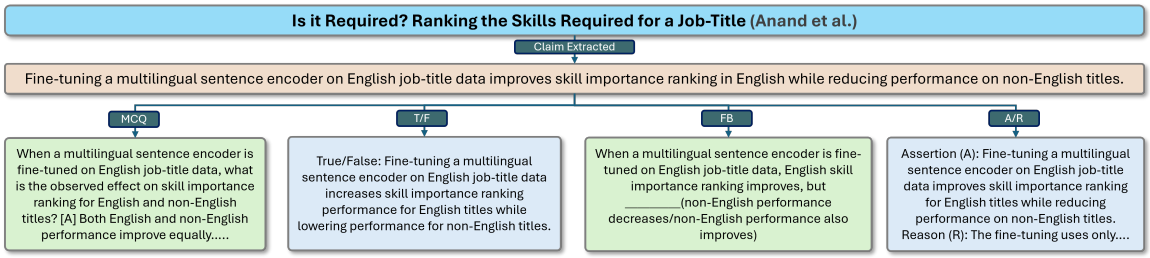


Figure 2: Example claim and QA in SciUnlearn dataset.

models ensure that the targeted claims are likely embedded in pretrained models, enabling meaningful evaluation. We further validate this assumption using likelihood-based membership signals and answer-order perturbations (App. H). The benchmark consists of a computer science dataset $\mathcal{D}_{\text{cs}}$, a medical dataset $\mathcal{D}_{\text{med}}$, and a retracted-paper dataset $\mathcal{D}_{\text{retracted}}$. The first two datasets cover domain-specific claim unlearning in active scientific fields, while $\mathcal{D}_{\text{retracted}}$ contains Dolma papers retracted after 2024 and identified using the Retraction Watch database (Retraction Watch, 2024). The full pipeline is shown in Fig. 1.

We sample 100 recent (2018–2022) open-access computer science papers from the Dolma corpus using the Semantic Scholar API (Kinney et al., 2023), forming $\mathcal{C}_f \subset \mathcal{C}$. For each paper $p \in \mathcal{C}_f$, we extract 1–5 claims $\mathcal{S}(p)$ using GPT-5[1] from the abstract, introduction, and conclusion[2]. We use an *LLM as a judge* to evaluate the extracted claims from all forget and retain set papers based on accuracy, independence, and clarity[2] on a 0–5 scale, using GPT-5.4, GPT-5.1 and Gemini-3.5-Flash[1]. Table 1 reports the percentage of cases in which at least two of the three models assign a score of 4 or higher out of 5. To validate LLM judgments, we correlate LLM scores with expert annotations on 75 claims from 50 randomly selected papers (App. B). Among these 50 papers, 24 are from computer science, 13 from medical science, and 13 from the retracted-paper set. We report Gwet's AC2 instead of Cohen's kappa because Cohen's kappa is susceptible to the kappa paradox under highly imbalanced ratings. As shown in Table 2, Gwet's AC2 indicates high human–LLM agreement across accuracy, independence, and clarity, supporting LLM-based evaluation as a scalable proxy for human scoring.

[1]Models are accessed via API with temperature = 1.0, top-p = 0.9, and a maximum input length of 40,000 characters.

[2]The detailed prompts used are given in https://github.com/snigdhapaul2003/Scientific-Claim-Unlearning/prompts.txt.

Domain	Accuracy	Independence	Clarity
CS	95.31%	99.71%	99.71%
Medical	95.03%	98.01%	99.67%
Retracted	92.57%	96.28%	99.32%

Table 1: Multi-LLM consensus rates for claim quality evaluation (% of claims with majority score ≥ 4).

Criterion	GPT-5.4	GPT-5.1	Gemini 3.5 Flash
Accuracy	0.90	0.91	0.84
Independence	0.88	0.86	0.87
Clarity	0.91	0.90	0.88

Table 2: Human–LLM agreement (Gwet's AC2)

For each claim $s \in \mathcal{S}(p)$, we generate eight (q, a) pairs—two each for MCQ, true/false(T/F), fill-in-the-blank(FB), and assertion–reason(AR)[2]. QA pairs are validated using OLMO-3-7B-Instruct ($\mathcal{M}$) with self-consistency checks (jin et al., 2024; Xie et al., 2025). Responses are evaluated using exact match, ROUGE (Lin, 2004), and semantic similarity (Reimers and Gurevych, 2019), with a threshold of 0.7 for non-exact matches. Claims with fewer than two valid question types are discarded. QA pairs are splitted into $\mathcal{F}_1$ and $\mathcal{F}_2$, as discussed in § 3. The statistical details of all subsets are presented in Table 3

Dataset	Papers	Claims	F1	F2	R_{ext}	R_{int}
$\mathcal{D}_{\text{cs}}$	76	170	536	536	1060	418
$\mathcal{D}_{\text{med}}$	78	127	508	508	908	543
$\mathcal{D}_{\text{retracted}}$	91	141	390	390	884	671

Table 3: Overview of the SciUnlearn datasets.

For $\mathcal{R}_{ext}$, we select for each $p \in \mathcal{P}$, the most semantically similar cited paper using SPECTER2 embeddings (Singh et al., 2023), extracting claims and QA pairs from each p. $\mathcal{R}_{int}$ is built from the same p using non–claim-specific, contextual QA pairs. We ensure no overlap between forget and retain sets (App. E). Fig. 2 shows an example, with full QA example provided in App. D. Final

Model	Method	Forget Set 1 ↓		Forget Set 2 ↓		Retain (Ext) ↑		Retain (Int) ↑		General Benchmarks		
		R-F1	EM	R-F1	EM	R-F1	EM	R-F1	EM	MMLU	Arc-C	HellaSwag
OLMO	Base Model	97.54	94.21	93.92	89.17	95.40	90.75	92.44	83.49	58.75	54.35	76.02
	GD ($\mathcal{F}_1$)	71.70	58.20	93.51	88.24	93.66	84.15	90.53	72.00	56.44	50.08	70.13
	NPO+RT ($\mathcal{F}_1$)	88.81	81.52	93.67	89.55	92.44	86.13	90.66	82.05	58.28	49.91	69.89
	GD ($\mathcal{F}_2$)	91.65	78.35	89.60	83.58	93.27	84.52	91.02	77.03	57.54	49.57	70.93
	NPO+RT ($\mathcal{F}_2$)	96.14	89.92	86.78	82.27	91.47	85.18	91.60	81.81	57.39	50.51	73.02
LLAMA	Base Model	96.61	93.65	87.37	77.61	91.86	86.03	90.07	83.25	64.74	75.58	55.88
	GD ($\mathcal{F}_1$)	78.33	74.06	88.32	80.03	85.45	80.37	89.00	83.25	63.01	73.91	46.67
	NPO+RT ($\mathcal{F}_1$)	73.56	70.33	90.91	86.38	86.53	83.01	90.35	83.73	63.35	75.28	53.41
	GD ($\mathcal{F}_2$)	93.31	88.80	59.18	37.87	76.78	65.47	81.31	73.20	60.93	74.30	47.69
	NPO+RT ($\mathcal{F}_2$)	96.08	93.09	78.59	66.23	87.36	78.86	85.14	77.27	64.44	75.01	55.37

Table 4: Results of LoRA unlearning using $\mathcal{F}_1$ and $\mathcal{F}_2$ for GD and NPO+RT on $\mathcal{D}_{\text{cs}}$. ↓ indicates lower is better (forgetting), while ↑ indicates higher is better (retention and generalization). OLMo-3-7B-Instruct is referred as OLMO and LLAMA3-8B-Instruct is referred as LLAMA. Additional method results are provided in App. L.

Model	Method	Forget Set 1 ↓		Forget Set 2 ↓		Retain (Ext) ↑		Retain (Int) ↑		General Benchmarks		
		R-F1	EM	R-F1	EM	R-F1	EM	R-F1	EM	MMLU	Arc-C	HellaSwag
OLMO	Base Model	92.16	78.59	84.59	65.96	87.74	71.14	92.49	81.95	58.76	54.35	76.02
	GD ($\mathcal{F}_1$)	58.20	35.78	75.40	61.05	86.78	73.78	92.77	84.34	57.24	52.47	71.07
	NPO+RT ($\mathcal{F}_1$)	83.09	67.36	83.93	68.07	89.69	74.77	92.49	85.63	59.50	52.73	75.30
	GD ($\mathcal{F}_2$)	83.80	68.77	55.59	32.28	88.97	74.77	93.95	86.37	56.43	51.70	72.50
	NPO+RT ($\mathcal{F}_2$)	92.52	85.64	73.89	51.53	91.96	85.06	94.79	88.07	59.14	53.41	73.54
LLAMA	Base Model	86.23	71.92	76.64	56.49	80.39	63.32	90.24	82.68	64.75	75.58	55.88
	GD ($\mathcal{F}_1$)	70.08	55.78	73.70	56.14	81.61	65.96	93.81	88.21	63.87	75.39	52.99
	NPO+RT ($\mathcal{F}_1$)	41.70	26.66	41.70	15.43	87.18	70.15	97.83	94.47	47.29	74.97	54.18
	GD ($\mathcal{F}_2$)	83.32	68.77	68.34	48.77	82.94	67.62	93.90	88.39	63.10	75.29	52.82
	NPO+RT ($\mathcal{F}_2$)	45.98	30.18	32.79	7.37	88.86	79.07	96.06	93.00	43.20	74.48	49.57

Table 5: Results of full parameter unlearning using $\mathcal{F}_1$ and $\mathcal{F}_2$ for GD and NPO+RT on $\mathcal{D}_{\text{med}}$. ↓ indicates lower is better (forgetting), while ↑ indicates higher is better (retention and generalization). OLMo-3-7B-Instruct is referred as OLMO and LLAMA3-8B-Instruct is referred as LLAMA.

statistics of SciUnlearn dataset are presented in Table 3. Detailed analysis on the Dataset is provided in App. C.

5 Experimental Set-up

We use OLMo-3-7B-Instruct (Groeneveld et al., 2024) for full-parameter and rank-8 LoRA training on a single 80 GB A100 GPU, and extended the experimentation with LLAMA-3-8B-Instruct. We benchmark representative approaches, including Gradient Difference (GD) (Neel et al., 2020), Negative Preference Optimization (NPO) (Zhang et al., 2024), NPO with retain objective (NPO+RT) (Bronec and Helcl, 2025), SimNPO (Fan et al., 2024), and SimNPO with retain set. All methods are applied to the pretrained model using forget sets $\mathcal{F}_1$ or $\mathcal{F}_2$. Implementation details and hyperparameters are provided in App. F and App. G. Task-specific performance is evaluated using Exact Match (EM) and ROUGE-L F1 (R-F1), capturing strict and paraphrase-tolerant correctness, respectively. General knowledge retention is assessed on MMLU, ARC-Challenge (AC), and HellaSwag (HS) (Hendrycks et al., 2020; Clark et al., 2018; Zellers et al., 2019), ensuring unlearning does not degrade overall language understanding.

6 Results

Table 4 presents the main LoRA results for GD and NPO+RT across both models on $\mathcal{D}_{\text{cs}}$, while additional LoRA methods are reported in App. L. Table 16 in App. M presents full-parameter unlearning results for the OLMO model on the dataset $\mathcal{D}_{\text{cs}}$. The full parameter unlearning results for both OLMO and LLAMA models on dataset $\mathcal{D}_{\text{med}}$ and $\mathcal{D}_{\text{retracted}}$ are provided in Table 5 and Table 6 respec-

Model	Method	Forget Set 1 ↓		Forget Set 2 ↓		Retain (Ext) ↑		Retain (Int) ↑		General Benchmarks		
		R-F1	EM	R-F1	EM	R-F1	EM	R-F1	EM	MMLU	Arc-C	HellaSwag
OLMO	Base Model	94.65	87.94	93.05	84.61	94.12	87.33	94.54	87.92	58.75	54.35	76.02
	GD ($\mathcal{F}_1$)	65.49	44.61	84.96	78.46	91.72	86.31	95.88	91.80	58.90	50.42	73.18
	NPO+RT ($\mathcal{F}_1$)	70.83	62.82	81.47	75.12	75.03	68.77	94.64	89.26	55.20	52.73	72.84
	GD ($\mathcal{F}_2$)	82.51	54.87	58.95	44.10	87.42	68.32	93.52	80.32	56.03	50.17	74.04
	NPO+RT ($\mathcal{F}_2$)	93.73	85.64	89.12	83.07	93.35	87.21	95.01	88.97	58.43	52.30	75.28
LLAMA	Base Model	88.63	84.61	88.12	76.15	90.43	83.71	96.53	92.69	64.75	75.58	55.89
	GD ($\mathcal{F}_1$)	72.34	67.94	85.51	75.38	90.86	84.95	97.06	94.48	64.71	75.50	53.66
	NPO+RT ($\mathcal{F}_1$)	36.96	33.07	35.69	12.82	81.23	66.17	94.90	80.47	51.05	74.90	50.50
	GD ($\mathcal{F}_2$)	88.11	80.25	68.27	59.23	92.45	86.99	97.89	96.57	63.38	75.37	53.92
	NPO+RT ($\mathcal{F}_2$)	48.25	44.35	24.43	1.79	92.02	80.76	98.78	96.27	56.42	74.67	49.23

Table 6: Results of full parameter unlearning using $\mathcal{F}_1$ and $\mathcal{F}_2$ for GD and NPO+RT on $\mathcal{D}_{\text{retracted}}$. ↓ indicates lower is better (forgetting), while ↑ indicates higher is better (retention and generalization). OLMo-3-7B-Instruct is referred as OLMO and LLAMA3-8B-Instruct is referred as LLAMA.

tively. The results show that forgetting is largely localized to the unlearned forget set, with minimal transfer to the other set. When unlearning is applied to $\mathcal{F}_1$ or $\mathcal{F}_2$, all representative methods significantly reduce performance on the targeted set leaving the counterpart largely unaffected. A complementary evaluation on open-ended questions provides preliminary evidence that the unlearning effect also extends beyond structured QA formats (App. I). Qualitative analysis (App. N) indicates that simpler QA formats (e.g., T/F and AR) and higher numbers of paraphrased QAs, and non deeply rooted papers amplify forgetting. However, none of the methods causes sharp performance drops, likely due to LoRA-based fine-tuning (jin et al., 2024) and the rootedness of claims in the pretraining corpus. Overall, forgetting remains subset-specific, suggesting current methods suppress surface-level patterns rather than underlying claim-level knowledge. Retention differs across methods: GD, NPO+RT, and SimNPO+RT preserve strong performance on both external and internal retain sets, while NPO and SimNPO show larger retention drops due to the absence of an explicit retain objective. Even in case of LLAMA, there is a significant performance drop in all the sets. This indicates that retain-aware methods better protect non-target knowledge. General benchmarks are affected unevenly: NPO and SimNPO without retention cause notable MMLU degradation in OLMO and HellaSwag degradation in LLAMA, while GD, NPO+RT, and SimNPO+RT largely preserve performance. Reference-model scores show lower drift for semantic than direct members in all $\mathcal{D}_{\text{cs}}$, $\mathcal{D}_{\text{med}}$ and $\mathcal{D}_{\text{retracted}}$, while in case of MIA, Min-K% AUCs also weaken for semantic members, as shown in detail in Table 7. Details for are provided in App. J.

Table 7: Membership inference attack (MIA) results for OLMO using Gradient Descent (GD) unlearning. Higher Ref Score Mean indicates stronger forgetting, while an AUC closer to 0.5 indicates membership indistinguishability (Good Unlearning). Mem indicates Member Data (Target Forget Set) and Sem means Semantic Member Data (Complementary Forget Set)

Method	Data	Min-K AUC		Ref Score Mean	
		Mem	Sem	Mem	Sem
GD	CS F1	0.68	0.73	2.89	0.57
GD	CS F2	0.53	0.77	3.17	0.29
GD	Med F1	0.52	0.70	7.84	0.36
GD	Med F2	0.39	0.77	6.61	0.93
GD	Retracted F1	0.51	0.82	3.53	0.15
GD	Retracted F2	0.57	0.69	4.68	0.33

7 Conclusion

This work introduces Scientific Claim Unlearning and the SciUnlearn benchmark for evaluating whether LMs can forget scientific claims at the claim level, also proving it's applicability with real world retracted claim subset. Experiments show that existing unlearning methods mainly suppress the specific training instances used for unlearning, with limited transfer to paraphrased or complementary forget sets. Overall, our findings suggest that scientific claim unlearning requires algorithms and evaluations that go beyond surface-form suppression and target structured conceptual knowledge.

Limitations

This work has three main limitations. First, we evaluate representative optimization-based unlearning methods, but do not study mechanistic or representation-level unlearning approaches that may better target internal claim representations. Second, although we include a real-world retracted-paper subset, its sample size remains small, limiting the breadth of conclusions that can be drawn from this setting. Expanding this subset with more retracted or explicitly falsified findings across broader scientific domains such as medicine, biology, and chemistry is an important direction for future work. Third, our experiments are limited to 7B–8B models due to the computational cost of full-parameter unlearning, leaving the behavior of larger frontier-scale models for future investigation.

References

Titipat Achakulvisut, Chandra Bhagavatula, Daniel Acuna, and Konrad Kording. 2019. Claim extraction in biomedical publications using deep discourse model and transfer learning. *arXiv preprint arXiv:1907.00962*.

Atilla Kaan Alkan, Shashwat Sourav, Maja Jabłońska, Simone Astarita, Rishabh Chakrabarty, Nikhil Garuda, Pranav Khetarpal, Maciej Pi'oro, Dimitrios Tanoglidis, Kartheik G. Iyer, Mugdha S. Polimera, Michael J. Smith, Tirthankar Ghosal, Marc Huertas-Company, Sandor Kruk, Kevin Schawinski, and Ioana Ciucua. 2025. A survey on hypothesis generation for scientific discovery in the era of large language models. *ArXiv*, abs/2504.05496.

Lucas Bourtoule, Varun Chandrasekaran, Christopher A. Choquette-Choo, Hengrui Jia, Adelin Travers, Baiwu Zhang, David Lie, and Nicolas Papernot. 2019. Machine unlearning. *2021 IEEE Symposium on Security and Privacy (SP)*, pages 141–159.

Jan Bronec and Jindřich Helcl. 2025. Atyaephyra at SemEval-2025 task 4: Low-rank negative preference optimization. In *Proceedings of the 19th International Workshop on Semantic Evaluation (SemEval-2025)*, pages 1415–1422, Vienna, Austria. Association for Computational Linguistics.

Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan. 2016. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356:183 – 186.

Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *ArXiv*, abs/1803.05457.

Thomas Diggelmann, Jordan Boyd-Graber, Jannis Bulian, Massimiliano Ciaramita, and Markus Leippold. 2020. Climate-fever: A dataset for verification of real-world climate claims. *Preprint*, arXiv:2012.00614.

Michael Duan, Anshuman Suri, Niloofar Mireshghallah, Sewon Min, Weijia Shi, Luke S. Zettlemoyer, Yulia Tsvetkov, Yejin Choi, David Evans, and Hanna Hajishirzi. 2024. Do membership inference attacks work on large language models? *ArXiv*, abs/2402.07841.

David Exler, Manuel Raimann, Marc F. Münker, Maxim Rosin, Joaquin Eduardo Urrutia Gómez, Christof M. Niemeyer, Markus Reischl, and Luca Rettenberger. 2026. Llm-based scientific assistants for knowledge extraction: Which design choices matter? *Advanced Intelligent Discovery*.

Chongyu Fan, Jiancheng Liu, Licong Lin, Jinghan Jia, Ruiqi Zhang, Song Mei, and Sijia Liu. 2024. Simplicity prevails: Rethinking negative preference optimization for llm unlearning. *ArXiv*, abs/2410.07163.

Aniketh Garikaparthi, Manasi Patwardhan, Lovekesh Vig, and Arman Cohan. 2025. IRIS: Interactive research ideation system for accelerating scientific discovery. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations)*, pages 592–603, Vienna, Austria. Association for Computational Linguistics.

Hila Gonen and Yoav Goldberg. 2019. Lipstick on a pig: Debiasing methods cover up systematic gender biases in word embeddings but do not remove them. In *North American Chapter of the Association for Computational Linguistics*.

Juraj Gottweis, Wei-Hung Weng, Alexander Daryin, Tao Tu, Anil Palepu, Petar Sirkovic, Artiom Myaskovsky, Felix Weissenberger, Keran Rong, Ryutaro Tanno, Khaled Saab, Dan George Popovici, Jacob Blum, Fan Zhang, Katherine Chou, Avinatan Hassidim, Burak Gokturk, Amin Vahdat, Pushmeet Kohli, and 15 others. 2025. Towards an ai co-scientist. *ArXiv*, abs/2502.18864.

Dirk Groeneveld, Iz Beltagy, Evan Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, Shane Arora, David Atkinson, Russell Authur, Khyathi Chandu, Arman Cohan, Jennifer Dumas, Yanai Elazar, Yuling Gu, Jack Hessel, and 24 others. 2024. OLMo: Accelerating the science of language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15789–15809, Bangkok, Thailand. Association for Computational Linguistics.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Xiaodong Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. *ArXiv*, abs/2009.03300.

Hengrui Jia, Taoran Li, Jonas Guan, and Varun Chandrasekaran. 2025. The erasure illusion: Stress-testing the generalization of llm forgetting evaluation. *ArXiv*, abs/2512.19025.

Xue Jiang, Yihong Dong, Zheng Fang, Yingwei Ma, Tan Wang, Rongyu Cao, Binhua Li, Zhi Jin, Wenpin Jiao, Yongbin Li, and Ge Li. 2025. Large language model unlearning for source code. *ArXiv*, abs/2506.17125.

Xiaomeng Jin, Zhiqi Bu, Bhanukiran Vinzamuri, Anil Ramakrishna, Kai-Wei Chang, Volkan Cevher, and Mingyi Hong. 2025. Unlearning as multi-task optimization: A normalized gradient difference approach with an adaptive learning rate. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 11278–11294, Albuquerque, New Mexico. Association for Computational Linguistics.

Zhuoran jin, Pengfei Cao, Chenhao Wang, Zhitao He, Hongbang Yuan, Jiachun Li, Yubo Chen, Kang Liu, and Jun Zhao. 2024. Rwku: Benchmarking real-world knowledge unlearning for large language models. In *Advances in Neural Information Processing Systems*, volume 37, pages 98213–98263. Curran Associates, Inc.

Rodney Michael Kinney, Chloe Anastasiades, Russell Authur, Iz Beltagy, Jonathan Bragg, Alexandra Buraczynski, Isabel Cachola, Stefan Candra, Yoganand Chandrasekhar, Arman Cohan, Miles Crawford, Doug Downey, Jason Dunkelberger, Oren Etzioni, Rob Evans, Sergey Feldman, Joseph Gorney, David W. Graham, F.Q. Hu, and 29 others. 2023. The semantic scholar open data platform. *ArXiv*, abs/2301.10140.

Sylvain E. Lesné, Ming Teng Koh, Linda A. Kotilinek, Rakez Kayed, Charles G Glabe, Austin J. Yang, Michela Gallagher, and Karen H. Ashe. 2006. A specific amyloid-beta protein assembly in the brain impairs memory. *Nature*, 440 7082:352–7.

Long Li, Weiwen Xu, Jiayan Guo, Ruochen Zhao, Xingxuan Li, Yuqian Yuan, Boqiang Zhang, Yuming Jiang, Yifei Xin, Ronghao Dang, Yu Rong, Deli Zhao, Tian Feng, and Lidong Bing. 2025. Chain of ideas: Revolutionizing research via novel idea development with LLM agents. In *Findings of the Association for Computational Linguistics: EMNLP 2025*, pages 8971–9004, Suzhou, China. Association for Computational Linguistics.

Nathaniel Li, Alexander Pan, Anjali Gopal, Summer Yue, Daniel Berrios, Alice Gatti, Justin Li, Ann-Kathrin Dombrowski, Shashwat Goel, Long Phan, Gabriel Mukobi, Nathan Helm-Burger, Rassin R. Lababidi, Lennart Justen, Andrew Liu, Michael K. Chen, Isabelle Barrass, Oliver Zhang, Xiaoyuan Zhu, and 34 others. 2024. The wmdp benchmark: Measuring and reducing malicious use with unlearning. *ArXiv*, abs/2403.03218.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Sijia Liu, Yuanshun Yao, Jinghan Jia, Stephen Casper, Nathalie Baracaldo, Peter Hase, Xiaojun Xu, Yuguang Yao, Chris Liu, Hang Li, Kush R. Varshney, Mohit Bansal, Sanmi Koyejo, and Yang Liu. 2024. Rethinking machine unlearning for large language models. *Nature Machine Intelligence*, 7:181 – 194.

Yezi Liu, Hanning Chen, Wenjun Huang, Yang Ni, and Mohsen Imani. 2025. Lune: Efficient llm unlearning via lora fine-tuning with negative examples. *ArXiv*, abs/2512.07375.

Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, and David Ha. 2024. The ai scientist: Towards fully automated open-ended scientific discovery. *ArXiv*, abs/2408.06292.

Pratyush Maini, Zhili Feng, Avi Schwarzschild, Zachary C. Lipton, and J. Zico Kolter. 2024. Tofu: A task of fictitious unlearning for llms.

Aashiq Muhamed, Jacopo Bonato, Mona T. Diab, and Virginia Smith. 2025. SAEs can improve unlearning: Dynamic sparse autoencoder guardrails for precision unlearning in LLMs. *ArXiv*, abs/2504.08192.

Seth Neel, Aaron Roth, and Saeed Sharifi-Malvajerdi. 2020. Descent-to-delete: Gradient-based methods for machine unlearning. *ArXiv*, abs/2007.02923.

Alexander Novikov, Ngân Vũ, Marvin Eisenberger, Emilien Dupont, Po-Sen Huang, Adam Zsolt Wagner, Sergey Shirobokov, Borislav Kozlovskii, Francisco J. R. Ruiz, Abbas Mehrabian, M. Pawan Kumar, Abigail See, Swarat Chaudhuri, George Holland, Alex Davies, Sebastian Nowozin, Pushmeet Kohli, and Matej Balog. 2025. AlphaEvolve: A coding agent for scientific and algorithmic discovery. *arXiv preprint arXiv:2506.13131*.

Dae Hoon Park and Catherine Blake. 2012. Identifying comparative claim sentences in full-text scientific articles. In *Proceedings of the Workshop on Detecting Structure in Scholarly Discourse*, pages 1–9, Jeju Island, Korea. Association for Computational Linguistics.

Ronak Pradeep, Xueguang Ma, Rodrigo Nogueira, and Jimmy Lin. 2021. Scientific claim verification with VerT5erini. In *Proceedings of the 12th International Workshop on Health Text Mining and Information Analysis*, pages 94–103, online. Association for Computational Linguistics.

Aniket Pramanick, Yufang Hou, Saif M. Mohammad, and Iryna Gurevych. 2026. Claimflow: Tracing the evolution of scientific claims in nlp.

Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on*

Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Retraction Watch. 2024. Retraction watch database. http://retractiondatabase.org/. Accessed: 2024-05-20.

Patryk Rybak, Paweł Batorski, Paul Swoboda, and Przemysław Spurek. 2026. Rebel: Hidden knowledge recovery via evolutionary-based evaluation loop. *Preprint*, arXiv:2602.06248.

Weijia Shi, Anirudh Ajith, Mengzhou Xia, Yangsibo Huang, Daogao Liu, Terra Blevins, Danqi Chen, and Luke S. Zettlemoyer. 2023. Detecting pretraining data from large language models. *ArXiv*, abs/2310.16789.

Weijia Shi, Jaechan Lee, Yangsibo Huang, Sadhika Malladi, Jieyu Zhao, Ari Holtzman, Daogao Liu, Luke S. Zettlemoyer, Noah A. Smith, and Chiyuan Zhang. 2024. Muse: Machine unlearning six-way evaluation for language models. *ArXiv*, abs/2407.06460.

Amanpreet Singh, Mike D'Arcy, Arman Cohan, Doug Downey, and Sergey Feldman. 2023. SciRepEval: A multi-format benchmark for scientific document representations. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 5548–5566, Singapore. Association for Computational Linguistics.

Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Authur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, Valentin Hofmann, Ananya Jha, Sachin Kumar, Li Lucy, Xinxi Lyu, Nathan Lambert, Ian Magnusson, Jacob Morrison, Niklas Muennighoff, and 17 others. 2024. Dolma: an open corpus of three trillion tokens for language model pretraining research. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15725–15788, Bangkok, Thailand. Association for Computational Linguistics.

Chris Stokel-Walker. 2026. Scientists invented a fake disease. AI told people it was real. *Nature*, 652:559–561.

Xuemei Tang, Xufeng Duan, and Zhenguang Cai. 2025. Large language models for automated literature review: An evaluation of reference generation, abstract writing, and review composition. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing*, pages 1602–1617, Suzhou, China. Association for Computational Linguistics.

Sagar Uprety, Boyana Buyuklieva, and Prayag Tiwari. 2025. Using large language models for hypotheses and claims extraction from scientific literature. In *Companion Proceedings of the ACM on Web Conference 2025*, WWW '25, page 1645–1648, New York, NY, USA. Association for Computing Machinery.

Fabio Urbina, Filippa Lentzos, Cédric Invernizzi, and Sean Ekins. 2022. Dual use of artificial-intelligence-powered drug discovery. *Nature Machine Intelligence*, 4:189 – 191.

David Wadden, Shanchuan Lin, Kyle Lo, Lucy Lu Wang, Madeleine van Zuylen, Arman Cohan, and Hannaneh Hajishirzi. 2020. Fact or fiction: Verifying scientific claims. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7534–7550, Online. Association for Computational Linguistics.

Yike Wang, Shangbin Feng, Yulia Tsvetkov, and Hannaneh Hajishirzi. 2025. Sciencemeter: Tracking scientific knowledge updates in language models. *arXiv preprint arXiv:2505.24302*.

Xin Wei. 2023. Claimdistiller: Scientific claim extraction with supervised contrastive learning. In *EEKE/AII@JCDL*.

Linxi Xie, Xin Teng, Shichang Ke, Hongyi Wen, and Shengjie Wang. 2025. Reveal and release: Iterative llm unlearning with self-generated data. In *Conference on Empirical Methods in Natural Language Processing*.

Robert Yang. 2025. Unlearning as ablation: Toward a falsifiable benchmark for generative scientific discovery. *ArXiv*, abs/2508.17681.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. HellaSwag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, Florence, Italy. Association for Computational Linguistics.

Dawen Zhang, Pamela Finckenberg-Broman, Thong Hoang, Shidong Pan, Zhenchang Xing, Mark Staples, and Xiwei Xu. 2023. Right to be forgotten in the era of large language models: implications, challenges, and solutions. *AI and Ethics*, 5:2445 – 2454.

Ruiqi Zhang, Licong Lin, Yu Bai, and Song Mei. 2024. Negative preference optimization: From catastrophic collapse to effective unlearning. *ArXiv*, abs/2404.05868.

A Example of Retracted and Falsified Claims

This example illustrates a critical failure mode in modern language models: the persistence of outdated, retracted, or falsified scientific claims. Despite subsequent corrections in the scientific record, models such as OLMO-3-7B-Instruct (Groeneveld et al., 2024) may continue to generate responses that reflect superseded knowledge. As shown in Figure 3, the model produces confident outputs that do not adequately account for post-publication revisions or retractions.

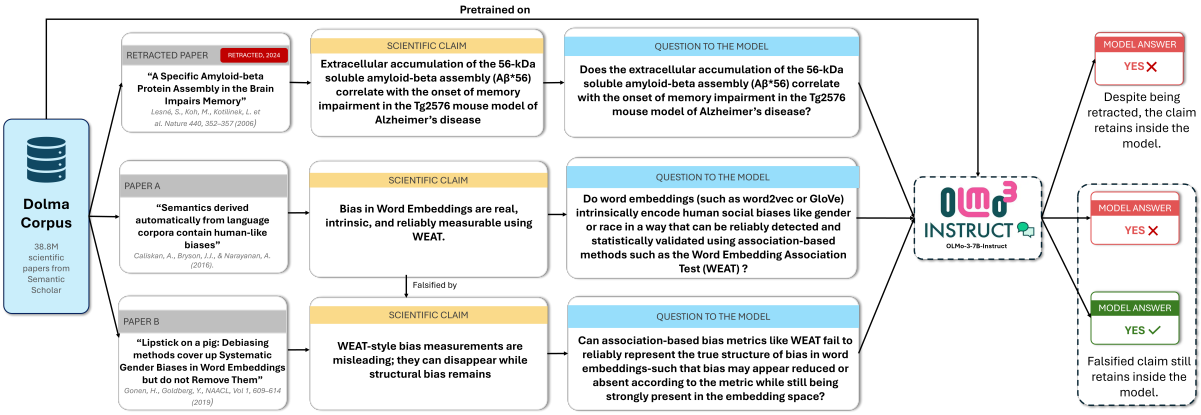
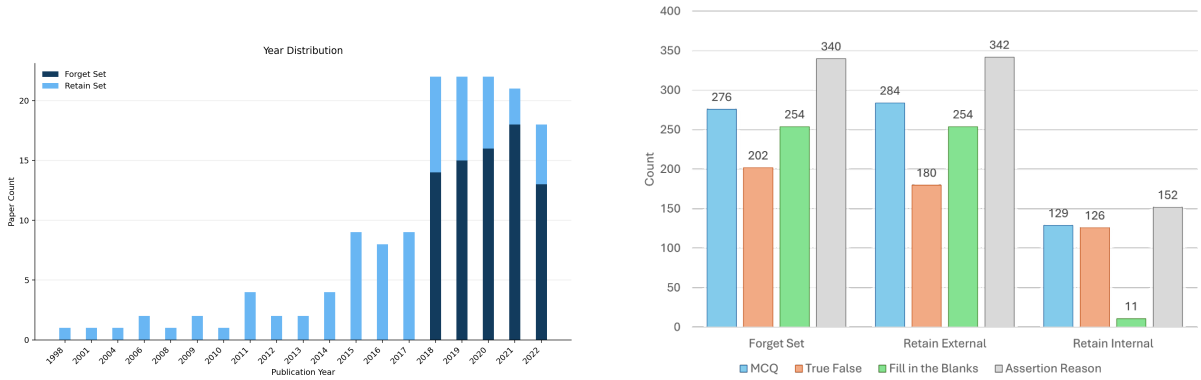


Figure 3: Failure case demonstrating the persistence of invalidated scientific knowledge in language models (OLMO-3-7B-Instruct (Groeneveld et al., 2024)).



(a) Year-wise distribution of questions

(b) Question type distribution

Figure 4: Dataset statistics for Computer Science subset. (a) Year-wise distribution of questions. (b) Distribution across question types.

B Human LLM evaluation Scores

We present representative examples of scientific claims extracted from papers in the shared github itself in a pdf named *Human LLM Agreement* along with their corresponding LLM-based and human evaluation scores.

C Dataset Statistics

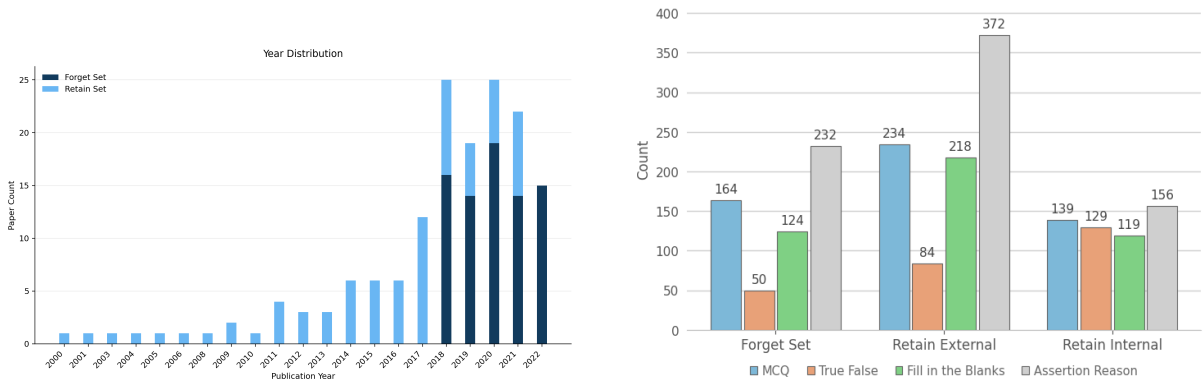
Figure 4a,5a, 6a shows the year-wise distribution of questions, which is skewed towards more recent papers for both the forget and retain sets. Figure 4b, 5b, 6b presents the question-type distribution, illustrating the diversity and relative frequency of different question categories present in the forget and retain sets. The total cost of dataset creation is approximately $36.57 over 2534 GPT-5 API calls.

D Sample Question-Answer

This section presents qualitative examples illustrating the end-to-end pipeline, including extracted scientific claims (Table 8 and 10), generated question-answer pairs (Table 9 and 11), and their evaluation from Computer Science subset. For each paper, we list the extracted claims, followed by representative question-answer pairs derived from a selected claim, verbatim statement from where the claim is taken, along with the reference answers, model predictions, and evaluation metrics for both forget and retain set.

E Distribution of Semantic Overlap Strength

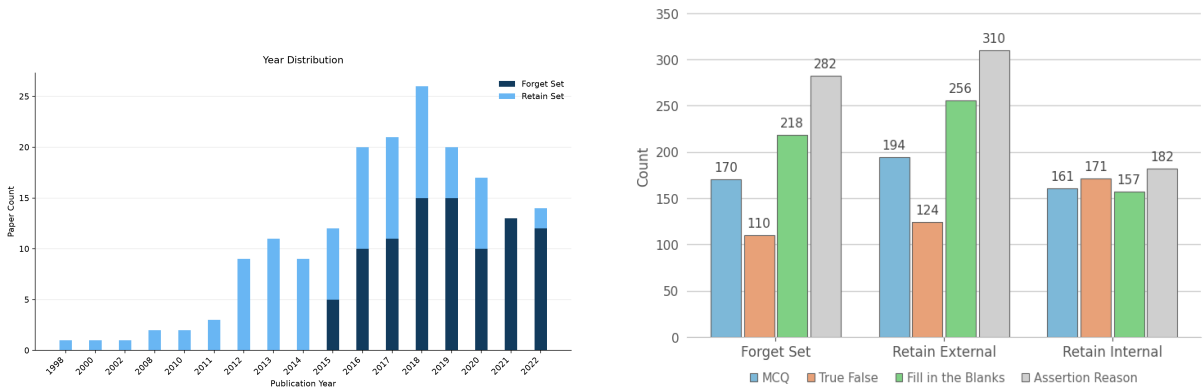
We analyze the extent of semantic overlap between the forget and retain sets, the distribution of the strongest non-self question similarity for each forget paper is examined. Here, non-self denotes all retain papers excluding the retain paper that directly corresponds to the anchor paper itself. For each forget paper, the maximum cosine similarity between any of its questions and all questions from non-corresponding retain papers was computed. This



(a) Year-wise distribution of questions

(b) Question type distribution

Figure 5: Dataset statistics for Medical subset. (a) Year-wise distribution of questions. (b) Distribution across question types.



(a) Year-wise distribution of questions

(b) Question type distribution

Figure 6: Dataset statistics for Retracted paper subset. (a) Year-wise distribution of questions. (b) Distribution across question types.

yields a single "best non-self similarity" score per paper, capturing the strongest potential semantic overlap. Figure 7 shows the distribution of these scores across all forget papers. An empirical threshold of $\tau = 0.8$ is used to define significant semantic overlap.

The distribution is concentrated in the range of approximately 0.45 to 0.65, with a mean similarity around 0.53. Importantly, no forget paper reaches or exceeds the threshold of 0.8, indicating the absence of high-confidence semantic overlap between the forget and retain sets. The absence of high-similarity matches confirms that the retain set is effectively disjoint from the forget set at a semantic level. This validates the dataset construction process and ensures that any observed unlearning behavior cannot be attributed to direct leakage or duplication across the two sets.

F Implementation Details

F.1 Gradient Difference (GD)

Gradient Difference modifies model parameters by performing gradient descent on the retain set while simultaneously performing gradient ascent on the forget set, thereby reducing the likelihood of generating target forget data (Neel et al., 2020). The update rule is defined in Equation 2.

$$\theta' = \theta - \eta\, w_r \nabla_\theta \mathcal{L}_{retain}(\theta) + \eta\, w_f \nabla_\theta \mathcal{L}_{forget}(\theta) \tag{2}$$

where θ represents model parameters, η is the learning rate, $\mathcal{L}_{forget}$ denotes the loss on the forget set, and $\mathcal{L}_{retain}$ denotes the loss on a retain set to preserve useful knowledge.

F.2 Negative Preference Optimization (NPO)

Negative Preference Optimization (Zhang et al., 2024; Bronec and Helcl, 2025) formulates unlearn-

Field	Content
Forget Paper Title	Is it Required? Ranking the Skills Required for a Job-Title
Extracted Claim	Fine-tuning a multilingual sentence encoder on English job-title data improves skill importance ranking in English while reducing performance on non-English titles.
Verbatim Claim	The model also performs fairly on other languages (as seen in the table 3), but by fine tuning we lose the multilingual capabilities of the ranking system.

Table 8: Forget-set claim used for sample QA generation from Computer Science subset.

Type	Question	Reference	OLMo	Metrics
MCQ 1	Choose the correct option (A–D): When a multilingual sentence encoder is fine-tuned on English job-title data, what is the observed effect on skill importance ranking for English and non-English titles? [A] Both English and non-English performance improve equally [B] English skill importance ranking improves, but performance on non-English titles decreases [C] English performance decreases while non-English improves [D] There is no measurable change in either English or non-English performance	B	B	EM=1.0, ROUGE=1.0, SemSim=1.0
MCQ 2	Choose the correct option (A–D): Fine-tuning a multilingual sentence encoder using only English job-title data leads to which outcome in skill importance ranking across languages? [A] Improvement limited to non-English titles with no change in English [B] Degradation for both English and non-English titles [C] Improved English results coupled with reduced performance on non-English titles [D] No trade-off; both English and non-English results improve	C	C	EM=1.0, ROUGE=1.0, SemSim=1.0
True/False 1	Fine-tuning a multilingual sentence encoder on English job-title data increases skill importance ranking performance for English titles while lowering performance for non-English titles.	True	True	EM=1.0, ROUGE=1.0, SemSim=1.0
True/False 2	Fine-tuning a multilingual sentence encoder on English job-title data improves skill importance ranking performance for both English and non-English titles.	False	False	EM=1.0, ROUGE=1.0, SemSim=1.0
Fill-in-the-blank 1	When a multilingual sentence encoder is fine-tuned on English job-title data, English skill importance ranking improves, but _____ (non-English performance decreases/non-English performance also improves).	non-English performance decreases	non-English performance decreases	EM=1.0, ROUGE=1.0, SemSim=1.0
Fill-in-the-blank 2	Fine-tuning a multilingual sentence encoder using English job-title data produces a trade-off: better English skill importance ranking and _____ (worse non-English performance/unchanged non-English performance).	worse non-English performance	worse non-English performance	EM=1.0, ROUGE=1.0, SemSim=1.0
Assertion–Reason 1	Assertion (A): Fine-tuning a multilingual sentence encoder on English job-title data improves skill importance ranking for English titles while reducing performance on non-English titles. Reason (R): The fine-tuning uses only English job-title examples, not multilingual data.	A is True, R is True, and R explains A.	A is True, R is True, and R explains A.	EM=1.0, ROUGE=1.0, SemSim=1.0
Assertion–Reason 2	Assertion (A): Fine-tuning a multilingual sentence encoder on English job-title data yields improved English skill importance ranking alongside reduced performance on non-English titles. Reason (R): Because the model is perfectly multilingual, English-only fine-tuning cannot hurt non-English performance.	A is True, R is False	A is True, R is False	EM=1.0, ROUGE=1.0, SemSim=1.0

Table 9: Sample forget-set QA pairs generated from the claim in Table 8.

ing as a preference learning problem, where the model is encouraged to prefer retained responses over those associated with the forget set. The objective is given in Equation 3.

$$\mathcal{L}_{\text{NPO}} = -\frac{2}{\beta}\,\mathbb{E}_{(x,y_f)}\left[\log\sigma\left(\beta\,\log\frac{p_{\theta_0}(y_f|x)}{p_\theta(y_f|x)}\right)\right] \tag{3}$$

where $p_\theta(y|x)$ denotes the conditional likelihood of generating response y given input x under the model parameterized by θ, and $p_{\theta_0}(y|x)$ denotes the corresponding likelihood under the reference (pretrained) model, which remains fixed during training. y_f denotes responses corresponding to the forget set, $\sigma(\cdot)$ is the sigmoid function, β is a scaling parameter controlling the sharpness of the preference.

F.3 NPO with Retain Set Fine-Tuning

To improve stability and mitigate unintended degradation of useful knowledge, the NPO objective is augmented with an additional retain set optimization. While NPO suppresses the likelihood of forget samples relative to a reference model, it does not explicitly enforce the preservation of retained knowledge. Therefore, a complementary retain objective is introduced.

The retain loss is defined in Equation 4.

$$\mathcal{L}_{retain} = -\mathbb{E}_{(x,y_r)}\left[\log p_\theta(y_r|x)\right] \tag{4}$$

The overall training objective is given in Equation 5.

$$\mathcal{L} = \lambda_{\text{NPO}}\mathcal{L}_{\text{NPO}} + \lambda_r\mathcal{L}_{retain} \tag{5}$$

where λ_{NPO} and λ_r control the relative contributions of the unlearning and retention objectives, respectively.

F.4 SimNPO (Simplified Negative Preference Optimization)

SimNPO (Fan et al., 2024) is a simplified variant of preference-based unlearning that operates without a

Field	Content
Retain Paper Title	JobBERT: Understanding Job Titles through Skills
Extracted Claim	Semantic representations of job titles learned by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, using token-level gating and negative sampling, enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and outperform generic sentence encoders on this task.

Table 10: Retain-set claim used for sample QA generation from Computer Science subset.

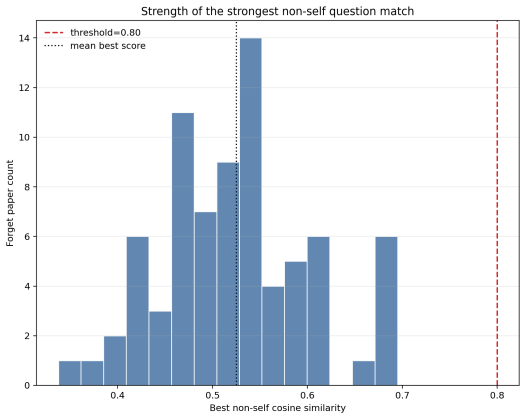


Figure 7: Distribution of the strongest non-self cosine similarity for each forget paper. The red dashed line indicates the overlap threshold ($\tau = 0.8$), and the black dotted line denotes the mean similarity.

reference model or explicit retain objective. Unlike standard NPO, which compares the current model against a fixed reference, SimNPO directly penalizes the likelihood of generating forget samples, making it a fully self-contained and reference-free unlearning approach. The objective is defined in Equation 6.

$$\mathcal{L}_{\text{SimNPO}} = -\frac{2}{\beta}\,\mathbb{E}_{(x,y_f)}\left[\log\sigma\left(-\beta\,\log p_\theta(y_f|x) - \gamma\right)\right], \tag{6}$$

where $p_\theta(y_f|x)$ denotes the average log-likelihood of the response y_f given input x, computed over answer tokens only. Here, $\sigma(\cdot)$ is the sigmoid function, β controls the sharpness of the penalty, and γ is a margin term.

This formulation directly encourages the model to reduce the likelihood of forget samples without relying on external comparisons or paired preferences. By operating on the average log-probability over answer tokens, SimNPO focuses on suppressing the generation of target responses at a sequence level.

F.5 SimNPO with Retain Set Fine-Tuning (SimNPO+RT)

To alleviate unintended forgetting and better preserve useful knowledge, SimNPO is extended with an explicit retain set objective. While SimNPO effectively suppresses forget samples by directly penalizing their likelihood, it does not impose any constraint to maintain performance on retained data. To address this limitation, a retain loss is incorporated alongside the SimNPO objective.

The retain loss is defined identically to Equation 4.Thus the combined SimNPO+RT objective is then given in Equation 7

$$\mathcal{L} = \lambda_{\text{SimNPO}}\mathcal{L}_{\text{SimNPO}} + \lambda_r\mathcal{L}_{\text{retain}}, \tag{7}$$

Here, λ_{SimNPO} and λ_r balance the contributions of the unlearning and retention objectives, respectively. By explicitly encouraging correct predictions on the retain set, SimNPO+RT improves training stability and helps maintain overall model utility while remaining free of reference-model comparisons.

G Hyperparameter Selection for Algorithm Implementation

As shown in Table 12, hyperparameters are chosen specifically to balance the trade-off between forgetting and retention, ensuring that the unlearning process effectively removes targeted information while preserving performance on retained data. Values are selected to achieve sufficient forgetting without inducing over-forgetting, which would unnecessarily degrade retained knowledge, thereby maintaining an optimal equilibrium between removal efficacy and utility preservation. Besides, different algorithms require distinct hyperparameters due to inherent differences in their unlearning dynamics and sensitivity to the forgetting–retention trade-off.

Type	Question	Reference	OLMo	Metrics
MCQ 1	Choose the correct option (A–D): Which statement correctly describes how semantic representations of job titles are learned and what they achieve? [A] Representations are learned by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, using token-level gating and negative sampling; they enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and outperform generic sentence encoders on this task. [B] Representations are learned by an LSTM-based encoder trained with manual title labels, without token-level gating or negative sampling; they enable taxonomy-specific normalization via rule-based matching and do not outperform generic sentence encoders on this task. [C] Representations are learned by a BERT-based encoder trained to predict job titles from skills, using token-level gating but no negative sampling; they require manual title labels for normalization and show performance comparable to generic sentence encoders. [D] Representations are obtained by unsupervised averaging of word embeddings from vacancy texts; they support taxonomy-agnostic cluster-based normalization but only match the performance of generic sentence encoders on this task.	A	A	EM=1.0, ROUGE=1.0, SemSim=1.0
MCQ 2	Choose the correct option (A–D): What configuration yields job-title representations that enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and surpass generic sentence encoders on that task? [A] Unsupervised averaging of token embeddings from vacancy texts with cluster-based normalization and no negative sampling. [B] A BERT-based encoder trained to reconstruct titles from taxonomies using manual labels, with attention but no negative sampling. [C] A BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, using token-level gating and negative sampling. [D] A generic sentence encoder fine-tuned on unrelated corpora with taxonomy-specific nearest-centroid mapping.	C	C	EM=1.0, ROUGE=1.0, SemSim=1.0
True/False 1	Semantic representations of job titles learned by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, using token-level gating and negative sampling, enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and outperform generic sentence encoders on this task.	True	True	EM=1.0, ROUGE=1.0, SemSim=1.0
True/False 2	Semantic representations of job titles learned by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, without token-level gating or negative sampling, require manual title labels for taxonomy-specific nearest-neighbor normalization and do not outperform generic sentence encoders on this task.	False	False	EM=1.0, ROUGE=1.0, SemSim=1.0
Fill-in-the-blank 1	The learned job-title representations support _____ (taxonomy-agnostic/taxonomy-specific) nearest-neighbor normalization without manual title labels and outperform generic sentence encoders, given they are produced by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts using token-level gating and negative sampling.	taxonomy-agnostic	taxonomy-agnostic	EM=1.0, ROUGE=1.0, SemSim=1.0
Fill-in-the-blank 2	Semantic representations of job titles produced by a _____ (BERT-based/LSTM-based) encoder trained with distant supervision to predict co-occurring skills from vacancy texts, with token-level gating and negative sampling, enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and outperform generic sentence encoders on this task.	BERT-based	BERT-based	EM=1.0, ROUGE=1.0, SemSim=1.0
Assertion–Reason 1	Assertion (A): Semantic representations of job titles learned by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, using token-level gating and negative sampling, enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and outperform generic sentence encoders on this task. Reason (R): Predicting co-occurring skills from vacancy texts under distant supervision aligns representations with job-title semantics, and token-level gating plus negative sampling increases discriminative power.	A is True, R is True, and R explains A.	A is True, R is True, and R explains A.	EM=1.0, ROUGE=1.0, SemSim=1.0
Assertion–Reason 2	Assertion (A): Semantic representations of job titles learned by a BERT-based encoder trained with distant supervision to predict co-occurring skills from vacancy texts, using token-level gating and negative sampling, enable taxonomy-agnostic nearest-neighbor normalization without manual title labels and outperform generic sentence encoders on this task. Reason (R): Manual title labels and taxonomy-specific rules are required for training and normalization in this setting.	A is True, R is False	A is True, R is False	EM=1.0, ROUGE=1.0, SemSim=1.0

Table 11: Sample retain-set QA pairs generated from the claim in Table 10.

H Distinguishing Memorization from General Reasoning

Correct QA performance alone does not establish that a model has memorized the underlying content, particularly for multiple-choice questions that may sometimes be answered through general reasoning or surface-level cues. We therefore conduct two complementary analyses to assess whether Sci-Unlearn measures knowledge acquired during pretraining rather than reasoning ability alone.

Likelihood-based membership signals. Following prior work on detecting pretraining data (Shi et al., 2023), we compare benchmark samples sourced from Dolma (members) with 97 samples drawn from papers published in 2025 and therefore absent from the Dolma corpus (non-members). The two groups exhibit a clear separation. Member samples have a substantially lower average negative log-likelihood (NLL) than non-members (0.24 vs. 3.88) and a higher Min-K% token-probability score at $K = 20\%$ (0.73 vs. 0.47). Thus, OLMo assigns markedly higher likelihood to the benchmark samples, providing evidence that their content was encountered during pretraining.

Robustness to answer-order perturbations. We additionally test whether MCQ performance depends on answer-position cues. For a subset of 10 four-option questions, we enumerate all $4! = 24$ permutations of the answer choices, producing 240 variants in total, following the answer-order intervention used by Muhamed et al. (2025). Before unlearning, the model answers 227 of the 240 variants correctly (94.6%), consistently selecting the same answer content despite changes in its position. This result rules out a fixed answer-position preference and demonstrates stable access to question-specific knowledge across nearly all orderings.

After unlearning, accuracy falls to 114 of 240

Param	GD		NPO		NPO+RT		SimNPO		SimNPO+RT	
	$\mathcal{F}_1$	$\mathcal{F}_2$	$\mathcal{F}_1$	$\mathcal{F}_2$	$\mathcal{F}_1$	$\mathcal{F}_2$	$\mathcal{F}_1$	$\mathcal{F}_2$	$\mathcal{F}_1$	$\mathcal{F}_2$
LR	$2e-5$	$1e-5$	$1e-5$	$1e-5$	$1e-5$	$1e-5$	$2e-5$	$2e-5$	$2e-5$	$2e-5$
Epochs	50	10	10	10	30	15	15	15	30	10
β	–	–	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
γ	–	–	–	–	–	–	0.0	0.0	0.0	0.0
w_f, w_r	(1.0, 3.0)	(1.2, 1.5)	(1.0, 0.0)	(1.0, 0.0)	(1.0, 4.0)	(1.2, 0.75)	(1.0, 4.0)	(1.0, 4.0)	(1.0, 4.0)	(1.0, 0.25)

Table 12: Hyperparameters for unlearning methods under forget sets $\mathcal{F}_1$ and $\mathcal{F}_2$. LR is Learning Rate; β is preference strength in NPO; γ scales retain regularization in SimNPOs; w_f and w_r is weights for forget and retain objectives.

variants (47.5%), a decrease of 47.1 percentage points. Because this reduction persists across all answer positions, it is unlikely to be explained solely by a change in positional preference. Instead, the result indicates that unlearning weakens the model's ability to retrieve the targeted information consistently.

Neither analysis alone can definitively separate memorization from every form of generalization. Taken together, however, the strong member–non-member separation in likelihood-based signals and the large, order-invariant decline after unlearning provide independent evidence that SciUnlearn captures knowledge acquired from the pretraining corpus and is therefore an appropriate setting for evaluating scientific claim unlearning.

I Free-Form Generation Evaluation

To examine whether the observed unlearning effects extend beyond structured QA formats, we conduct a small-scale free-form generation experiment. We construct 50 open-ended questions from 50 claims in the computer science dataset and apply Gradient Difference (GD) unlearning to OLMo. Because exact-match and ROUGE scores are poorly suited to open-ended responses with multiple valid surface forms, we evaluate the likelihood assigned to the target answers using negative log-likelihood (NLL) and Min-K% token probability.

Metric	Base Model	Unlearned Model
Mean NLL	1.39	2.59
Median NLL	1.37	2.19
Mean Min-K% prob.	0.58	0.47
Median Min-K% prob.	0.57	0.48

Table 13: Free-form generation results on 50 open-ended questions before and after GD unlearning. Higher NLL and lower Min-K% probability indicate reduced likelihood of the target information.

As shown in Table 13, unlearning increases both mean and median NLL, while decreasing the corresponding Min-K% token-probability statistics. The mean NLL rises from 1.39 to 2.59 and the mean Min-K% probability falls from 0.58 to 0.47, indicating that the unlearned model assigns lower likelihood to the targeted information. Although this experiment is limited to 50 questions and one model–algorithm configuration, it provides preliminary evidence that the unlearning effect extends beyond structured QA evaluation to free-form generation.

J Reference Score Drift and Membership Inference Attack

To further analyze whether unlearning transfers beyond the explicitly targeted forget subset, we conduct an additional membership inference analysis (Duan et al., 2024) using both direct members and *semantic members*. Due to computational and time constraints, we restrict this analysis to the strongest-performing configuration in our experiments, namely GD on $\mathcal{F}_1$. Unlike conventional MIA settings, our goal is not only to distinguish members from non-members, but also to study whether semantically related claims from the complementary forget subset $\mathcal{F}_2$ exhibit membership-like behavior after unlearning. This allows us to evaluate whether forgetting propagates beyond the directly unlearned samples.

Specifically, we define three groups: (i) **Member**: QA pairs originating from the directly unlearned forget subset $\mathcal{F}_1$, (ii) **Semantic Member**: semantically related QA pairs from $\mathcal{F}_2$, and (iii) **Non-member**: unrelated external QA samples not involved in training or unlearning.

The semantic-member setup differs from traditional MIA formulations, where the objective is usually binary member vs. non-member discrimination. Here, semantic members are intentionally introduced to probe the locality and transferability of forgetting.

We evaluate two signals: Min-K% probability and reference-model score.

(1) Min-K% Probability We further compute the Min-K% score proposed in prior memorization studies:

$$\text{MinK}(x) = \frac{1}{|S_k|} \sum_{t \in S_k} \log p_\theta(y_t \mid x, y_{<t}),$$

where S_k denotes the bottom-k% least confident output tokens. We use $k = 20\%$ following prior work. Less negative values indicate stronger membership behavior.

(2) Reference Model Score To quantify drift relative to the original pretrained model, we compute:

$$\text{RefScore}(x) = \mathcal{L}_{\text{unlearned}}(x) - \mathcal{L}_{\text{base}}(x).$$

Scores near zero indicate that the unlearned model behaves similarly to the original base model, whereas larger positive values indicate stronger forgetting-induced deviation.

Table 7 shows that direct members exhibit stronger forgetting signatures than semantic members. Overall, the MIA results indicate that forgetting is mostly localized to $\mathcal{F}_1$ and transfers only weakly to semantically related claims in $\mathcal{F}_2$ and vice versa.

K Examples of Unlearning Across Algorithms

To demonstrate the effectiveness of unlearning, we present representative examples from the forget set in Table 14 for Computer Science subset. All algorithms consistently produce incorrect outputs, indicating successful forgetting.

L Additional LoRA Results

Additional experimentation on LORA based unlearning with NPO, SimNPO and SimNPO+RT are shown in Table 15.

M Full Parameter Unlearning

For OLMO model each unlearning algorithm (full parameter unlearning) the result is shown in Table 16 for all experimental setting (i.e., training with Forget Set 1 and Forget Set 2).

N Qualitative Analysis of Unlearning

This section presents a detailed qualitative analysis of unlearning across Gradient Difference (GD), NPO+RT, and SimNPO+RT under both Forget Set 1 and Forget Set 2 training settings with Computer Science subset. The analysis combines quantitative error distributions with behavioral observations to understand how unlearning manifests at the level of scientific claims.

N.1 Error Distribution Across Question Formats

As shown is Table 17, across all methods, error rates are significantly higher on the forget set used during unlearning, indicating effective degradation on seen instances. However, when evaluated on a disjoint forget set, error rates drop sharply. This suggests that unlearning does not generalize well to semantically equivalent but differently phrased questions, and remains largely confined to the exact training instances.

Unlearning effectiveness varies across question formats. Structured formats such as True/False and Assertion/Reason exhibit higher error rates, indicating stronger forgetting. In contrast, MCQ and Fill-in-the-blank formats show relatively lower degradation, suggesting that these formats require deeper semantic understanding and are more resistant to unlearning. Overall, current methods appear to induce surface-level suppression rather than removing underlying claim-level knowledge.

Analysis on retain sets reveals a consistent pattern across methods. The highest degradation is observed for Fill-in-the-blank questions, followed by Assertion/Reason. MCQ questions are the most retained, while True/False lies in between. This indicates that retention is strongest for formats requiring recognition rather than generation.

A recurring failure mode is observed in Assertion–Reason questions, where the model struggles with explanation linkage. Although the model often correctly evaluates both the assertion and the reason individually, it fails to determine whether the reason logically explains the assertion.

- Reference: `A is True, R is True, and R explains A`
- Model: `A is True, R is True, but R does not explain A`

This behavior suggests that while factual knowledge is retained, the *relational structure* between

Example 1
Question: For Z24 Bridge natural frequency data, time-delay embeddings of the raw series exhibit a toroidal topology driven by cyclic temperature effects, whereas embeddings of cointegrated residuals exhibit an open-ball topology characteristic of approximately Gaussian white-noise processes. **Ground Truth:** True **GD:** False **NPO:** False **NPO+RT:** False **SimNPO:** False **SimNPO+RT:** False
Example 2
Question: When the second natural frequency depends nonlinearly on temperature, linear cointegration leaves residual topological structure, whereas Gaussian process-based nonlinear cointegration trained on data that include the nonlinear regime more effectively removes these effects. **Ground Truth:** True **GD:** False **NPO:** False **NPO+RT:** False **SimNPO:** False **SimNPO+RT:** False
Example 3
Question: In a linear classifier with an additive patch trigger, the optimal untargeted adversarial perturbation has a _____(substantial projection/near-zero projection) onto the trigger direction, theoretically explaining the similarity between adversarial and triggered inputs. **Ground Truth:** substantial **GD:** near-zero **NPO:** near-zero **NPO+RT:** near-zero **SimNPO:** near-zero **SimNPO+RT:** near-zero
Example 4
Question: Choose the correct option (A–D): When predicted skill importance scores are multiplied by the inverse document frequency of each skill, what is the resulting effect on ranking? [A] It enhances the ranking of specialized skills by penalizing generic skills. [B] It enhances the ranking of generic skills by penalizing specialized skills. [C] It leaves the ranking unchanged regardless of skill specificity. [D] It randomizes the ranking without regard to skill frequency. **Ground Truth:** A **GD:** B **NPO:** B **NPO+RT:** B **SimNPO:** B **SimNPO+RT:** B
Example 5
Question: Fine-tuning a multilingual sentence encoder on English job-title data increases skill importance ranking performance for English titles while lowering performance for non-English titles. **Ground Truth:** True **GD:** False **NPO:** False **NPO+RT:** False **SimNPO:** False **SimNPO+RT:** False

Table 14: Examples showing consistent incorrect responses across different unlearning algorithms.

concepts is degraded during unlearning.

N.2 Top Error-Prone Papers on Forget and Retain Sets

We analyze recurring error-prone papers separately for the forget and retain-external splits. Across both splits, errors concentrate on a small set of papers, suggesting that paper-level fragility and question design, rather than a single unlearning algorithm, drive many failures.

Forget set. A consistent subset of forget-set papers repeatedly appears among the most error-prone across algorithms:

- **Highly consistent across settings:** How to measure uncertainty in uncertainty sampling for active learning; Deep Insights into Convolutional Networks for Video Recognition; Math-word embedding in math search and semantic extraction; ReliefE: feature ranking in high-dimensional spaces via manifold embeddings.
- **Frequently appearing:** Is it Required? Ranking the Skills Required for a Job-Title; Hierarchical sparse Cholesky decomposition with applications to high-dimensional spatio-temporal filtering.
- **Moderately frequent:** Distributed deep learning platform for pedestrian detection on IT convergence environment; Disk Cluster Allocation Behavior in Windows and NTFS; Reducing false wake-up in contention-based wake-up control of wireless LANs; Approximation of quantum control correction scheme using deep neural networks.

These papers typically contain simple, atomic claims with a single decision boundary. Their repeated occurrence across methods indicates that errors arise from *intrinsic claim fragility* rather than algorithm-specific weaknesses.

Retain external set. For the retain-external split, we examine the most error-prone retained papers across algorithms and training settings:

Model	Method	Forget Set 1 ↓		Forget Set 2 ↓		Retain (Ext) ↑		Retain (Int) ↑		General Benchmarks		
		R-F1	EM	R-F1	EM	R-F1	EM	R-F1	EM	MMLU	Arc-C	HellaSwag
OLMO	NPO ($\mathcal{F}_1$)	83.77	73.50	87.26	76.11	83.75	72.83	87.12	77.03	39.38	41.21	69.98
	SimNPO ($\mathcal{F}_1$)	86.00	75.37	87.75	79.47	86.38	76.98	89.57	79.66	43.68	40.35	71.37
	SimNPO+RT ($\mathcal{F}_1$)	83.98	69.96	94.29	89.73	92.05	82.92	89.04	77.27	58.32	48.54	69.83
	NPO ($\mathcal{F}_2$)	94.18	81.15	73.87	54.47	84.58	67.92	87.26	77.51	27.73	41.55	70.36
	SimNPO ($\mathcal{F}_2$)	92.66	81.34	78.53	62.87	86.74	72.54	90.65	81.57	37.91	41.55	71.55
	SimNPO+RT ($\mathcal{F}_2$)	94.99	89.55	92.31	86.75	93.23	86.32	92.33	82.77	58.25	50.34	73.44
LLAMA	NPO ($\mathcal{F}_1$)	70.05	63.80	77.11	63.43	74.57	64.71	85.89	77.03	64.23	74.49	48.63
	SimNPO ($\mathcal{F}_1$)	76.97	70.33	77.58	62.87	77.70	66.98	88.75	80.86	64.54	75.02	49.31
	SimNPO+RT ($\mathcal{F}_1$)	85.66	81.52	88.40	80.41	90.13	85.00	89.69	81.33	64.49	75.10	50.85
	NPO ($\mathcal{F}_2$)	72.76	65.29	74.84	60.82	76.01	66.22	88.31	81.57	63.87	74.28	45.98
	SimNPO ($\mathcal{F}_2$)	77.06	70.70	75.92	62.68	77.63	66.79	88.48	81.10	64.67	75.21	49.31
	SimNPO+RT ($\mathcal{F}_2$)	95.68	92.72	76.32	60.63	85.87	75.09	86.54	77.99	64.76	75.69	52.81

Table 15: Additional LoRA unlearning results. OLMO indicates OLMo-3-7B-Instruct and LLAMA indicates LLAMA3-8B-Instruct

Method	Forget Set 1 ↓		Forget Set 2 ↓		Retain (Ext) ↑		Retain (Int) ↑		General Benchmarks		
	R-F1	EM	R-F1	EM	R-F1	EM	R-F1	EM	MMLU	Arc Challenge	HellaSwag
Base Model	97.54	94.21	93.92	89.17	95.40	90.75	92.44	83.49	58.75	54.35	76.02
GD ($\mathcal{F}_1$)	**71.33**	**55.59**	91.73	87.12	**95.68**	**93.01**	**93.70**	**85.40**	56.23	52.30	72.40
NPO ($\mathcal{F}_1$)	94.92	89.55	94.58	89.36	94.29	88.67	**92.87**	83.73	57.59	50.76	75.47
NPO+RT ($\mathcal{F}_1$)	81.41	74.81	93.98	90.11	91.33	83.20	90.70	75.83	57.71	52.30	75.00
SimNPO ($\mathcal{F}_1$)	96.26	91.23	93.94	89.36	94.18	88.77	92.84	82.77	58.24	**52.64**	**75.94**
SimNPO+RT ($\mathcal{F}_1$)	**73.45**	**64.73**	92.58	89.17	**94.84**	89.24	92.34	81.10	**58.96**	52.47	74.50
GD ($\mathcal{F}_2$)	95.57	92.35	**61.59**	**53.91**	94.61	**90.84**	92.79	**84.44**	56.05	49.65	64.63
NPO ($\mathcal{F}_2$)	96.78	91.79	87.01	78.54	92.89	86.03	91.74	82.29	57.45	51.87	75.66
NPO+RT ($\mathcal{F}_2$)	96.88	92.53	87.09	77.79	92.50	85.28	91.81	82.29	58.01	52.13	**75.73**
SimNPO ($\mathcal{F}_2$)	96.44	91.79	87.01	78.54	92.89	86.03	91.74	82.29	57.45	51.87	75.66
SimNPO+RT ($\mathcal{F}_2$)	96.09	92.35	**65.90**	**46.08**	92.11	83.11	92.37	82.05	**59.14**	**52.73**	72.45

Table 16: Full Parameter Unlearning with OLMo-3-7B-Instruct. R-F1(%): ROUGE-F1, EM(%): Exact Match, AC: Arc Challenge, HS: HellaSwag., ↓: lower is better (forgetting), and ↑: higher is better (retention and generalization), **Best** and **Second Best**

- **Appearing in all configurations:** An Empirical Study of Recent Face Alignment Methods; Dynamic SDN-Based Radio Access Network Slicing With Deep Reinforcement Learning for URLLC and eMBB Services.
- **Appearing in five out of six settings:** Towards Massively Parallel Computations in Algebraic Geometry; Recurrent Neural Networks with Top-k Gains for Session-based Recommendations; Efficient Non-greedy Optimization of Decision Trees; Adversarial Machine Learning for 5G Communications Security.

The same retained papers recur across algorithms because they are fragile items in the dataset, so different training setups affect the same weak points. This pattern suggests question-design sensitivity rather than simple topic difficulty: broad topic recognition often survives, while exact relation checking and phrase-level recall are more vulnerable.

N.3 Question Density Analysis of Error-Prone Papers

As shown in Table 18, the 10 most error-prone papers exhibit a substantially higher question density, with an average of 27.6 questions per paper. All selected papers lie above the dataset median, and 9 out of 10 exceed the 80th percentile, indicating that they are significantly overrepresented in terms of question coverage.

Among these, *Math-word embedding in math search and semantic extraction* is the most densely represented paper with 38 questions, corresponding to the 100th percentile. In contrast, *Disk Cluster Allocation Behavior in Windows and NTFS* has the lowest count among the selected set (14 questions), yet it still lies above the dataset median.

These findings indicate that highly represented

Method	Split	MCQ	True/False	Fill in the Blanks	Assertion Reason
GD trained on Forget Set 1					
GD-FS1	Forget Set 1	$21/138_{(15.2\%)}$	$68/101_{(67.3\%)}$	$49/127_{(38.6\%)}$	$86/170_{(50.6\%)}$
	Forget Set 2	$9/138_{(6.5\%)}$	$0/101_{(0.0\%)}$	$22/127_{(17.3\%)}$	$30/170_{(17.6\%)}$
	Retain_ext	$2/284_{(0.7\%)}$	$32/180_{(17.8\%)}$	$22/254_{(8.7\%)}$	$112/342_{(32.8\%)}$
	Retain_int	$0/129_{(0.0\%)}$	$14/126_{(11.1\%)}$	$9/11_{(81.8\%)}$	$94/152_{(61.8\%)}$
GD trained on Forget Set 2					
GD-FS2	Forget Set 1	$1/138_{(0.7\%)}$	$1/101_{(1.0\%)}$	$10/127_{(7.9\%)}$	$33/170_{(19.4\%)}$
	Forget Set 2	$4/138_{(2.9\%)}$	$50/101_{(49.5\%)}$	$15/127_{(11.8\%)}$	$35/170_{(20.6\%)}$
	Retain_ext	$8/284_{(2.8\%)}$	$40/180_{(22.2\%)}$	$32/254_{(12.6\%)}$	$72/342_{(21.1\%)}$
	Retain_int	$3/129_{(2.3\%)}$	$7/126_{(5.6\%)}$	$11/11_{(100.0\%)}$	$63/152_{(41.4\%)}$
NPO+RT trained on Forget Set 1					
NPO+RT-FS1	Forget Set 1	$7/138_{(5.1\%)}$	$35/101_{(34.7\%)}$	$25/127_{(19.7\%)}$	$32/170_{(18.8\%)}$
	Forget Set 2	$5/138_{(3.6\%)}$	$1/101_{(1.0\%)}$	$35/127_{(27.6\%)}$	$15/170_{(8.8\%)}$
	Retain_ext	$6/284_{(2.1\%)}$	$30/180_{(16.7\%)}$	$63/254_{(24.8\%)}$	$48/342_{(14.0\%)}$
	Retain_int	$3/129_{(2.3\%)}$	$13/126_{(10.3\%)}$	$11/11_{(100.0\%)}$	$48/152_{(31.6\%)}$
NPO+RT trained on Forget Set 2					
NPO+RT-FS2	Forget Set 1	$5/138_{(3.6\%)}$	$1/101_{(1.0\%)}$	$13/127_{(10.2\%)}$	$35/170_{(20.6\%)}$
	Forget Set 2	$2/138_{(1.4\%)}$	$47/101_{(46.5\%)}$	$25/127_{(19.7\%)}$	$21/170_{(12.4\%)}$
	Retain_ext	$10/284_{(3.5\%)}$	$37/180_{(20.6\%)}$	$51/254_{(20.1\%)}$	$59/342_{(17.3\%)}$
	Retain_int	$3/129_{(2.3\%)}$	$7/126_{(5.6\%)}$	$10/11_{(90.9\%)}$	$56/152_{(36.8\%)}$
SimNPO+RT trained on Forget Set 1					
SimNPO+RT-FS1	Forget Set 1	$13/138_{(9.4\%)}$	$38/101_{(37.6\%)}$	$33/127_{(26.0\%)}$	$77/170_{(45.3\%)}$
	Forget Set 2	$7/138_{(5.1\%)}$	$0/101_{(0.0\%)}$	$33/127_{(26.0\%)}$	$15/170_{(8.8\%)}$
	Retain_ext	$5/284_{(1.8\%)}$	$26/180_{(14.4\%)}$	$66/254_{(26.0\%)}$	$84/342_{(24.6\%)}$
	Retain_int	$4/129_{(3.1\%)}$	$14/126_{(11.1\%)}$	$11/11_{(100.0\%)}$	$66/152_{(43.4\%)}$
SimNPO+RT trained on Forget Set 2					
SimNPO+RT-FS2	Forget Set 1	$6/138_{(4.3\%)}$	$4/101_{(4.0\%)}$	$20/127_{(15.7\%)}$	$26/170_{(15.3\%)}$
	Forget Set 2	$3/138_{(2.2\%)}$	$12/101_{(11.9\%)}$	$30/127_{(23.6\%)}$	$26/170_{(15.3\%)}$
	Retain_ext	$12/284_{(4.2\%)}$	$13/180_{(7.2\%)}$	$54/254_{(21.3\%)}$	$66/342_{(19.3\%)}$
	Retain_int	$4/129_{(3.1\%)}$	$2/126_{(1.6\%)}$	$10/11_{(90.9\%)}$	$56/152_{(36.8\%)}$

Table 17: Unified error distribution across all methods and evaluation splits for $\mathcal{D}_{\text{cs}}$. Cells show errors / total (error rate %).

Paper	Questions	Percentile
How to measure uncertainty in uncertainty sampling for active learning	32	98.7
Deep Insights into Convolutional Networks for Video Recognition	30	94.7
Math-word embedding in math search and semantic extraction	38	100.0
ReliefE: feature ranking in high-dimensional spaces via manifold embeddings	28	89.5
Is it Required? Ranking the Skills Required for a Job-Title	26	86.8
Hierarchical sparse Cholesky decomposition with applications to high-dimensional spatio-temporal filtering	30	94.7
Distributed deep learning platform for pedestrian detection on IT convergence environment	32	98.7
Disk Cluster Allocation Behavior in Windows and NTFS	14	61.8
Reducing false wake-up in contention-based wake-up control of wireless LANs	20	81.6
Approximation of quantum control correction scheme using deep neural networks	26	86.8

Table 18: Question density statistics for the most error-prone papers.

papers are more likely to appear among the most error-prone cases, suggesting that both exposure frequency and claim density contribute to unlearning difficulty.

N.4 Analysis of Cross-Forget-Set Spillover in Unlearning

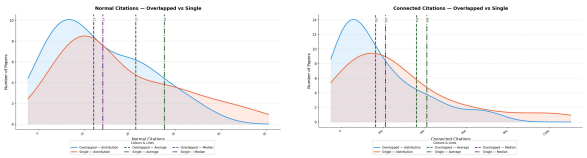
For a subset of papers, unlearning with one forget set induces measurable forgetting in the *other* forget set as well—yet this spillover does not occur universally. Understanding why some papers are susceptible to this cross-forget-set effect while others are not is the central question explored in subsection.

Table 19 reports, for each unlearning algorithm and forget-set configuration, how many papers exhibit errors (i.e. measurable forgetting) in **both** forget sets simultaneously, in **only** the first forget set, and in **only** the second forget set.

Algorithm / Config	Both	Only F1	Only F2	Total
GD F1	39	30	1	70
GD F2	30	5	25	60
NPO RT F1	29	20	7	56
NPO RT F2	28	13	23	64
SimNPO RT F1	32	31	3	66
SimNPO RT F2	29	9	15	53

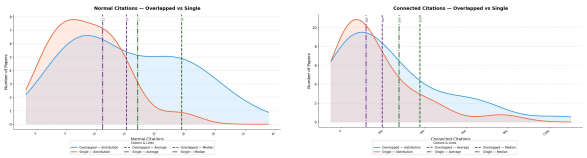
Table 19: Per-paper error distribution across the two forget sets for each unlearning algorithm and forget-set configuration. *Both* denotes papers showing forgetting in both sets; *Only F1* and *Only F2* denote papers showing forgetting exclusively in Forget Set 1 or Forget Set 2, respectively.

The pattern is consistent across all six algorithm–configuration combinations. This consistency suggests the susceptibility to spillover is a property of the *papers themselves* rather than an artefact of any particular unlearning algorithm.



(a) KDE Plot of normal citations (b) KDE Plot of connected citations

Figure 8: KDE plot for GD algorithm when unlearned with Forget Set 1.



(a) KDE Plot of normal citations (b) KDE Plot of connected citations

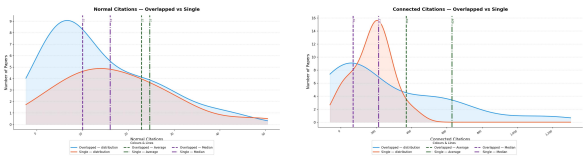
Figure 9: KDE plot for GD algorithm when unlearned with Forget Set 2.

N.4.1 Proxy Measure: Citation-Based Embeddedness

The natural hypothesis is that papers which are forgotten by *both* forget sets are less deeply embedded in the model's pretraining corpus—their knowledge representations are less reinforced by a wider neighbourhood of related content. Directly measuring how deeply a paper is rooted in a pretrained model's weights is intractable, however, as it would require exhaustive probing across the full parameter space.

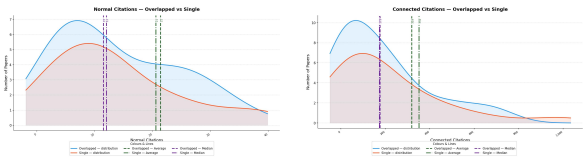
We therefore adopt two **proxy measures** derived from the Semantic Scholar citation graph.

1. **Normal citation count.** The number of papers that directly cite the paper under consideration. A highly-cited paper is more likely to have its findings reproduced, discussed, and cross-referenced in a large volume of text that would itself be present in a large pretrain-



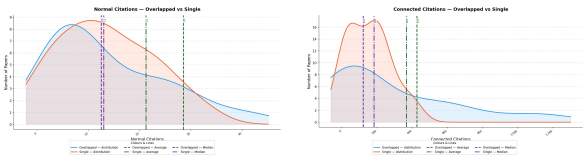
(a) KDE Plot of normal citations (b) KDE Plot of connected citations

Figure 10: KDE plot for NPO+RT algorithm when unlearned with Forget Set 1.



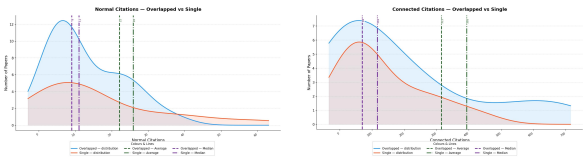
(a) KDE Plot of normal citations (b) KDE Plot of connected citations

Figure 11: KDE plot for NPO+RT algorithm when unlearned with Forget Set 2.



(a) KDE Plot of normal citations (b) KDE Plot of connected citations

Figure 12: KDE plot for SimNPO+RT algorithm when unlearned with Forget Set 1.



(a) KDE Plot of normal citations (b) KDE Plot of connected citations

Figure 13: KDE plot for SimNPO+RT algorithm when unlearned with Forget Set 2.

ing corpus. Consequently, the paper's content is represented not just once but implicitly through thousands of derivative works.

2. **Connected citation count.** Defined as the paper's own citation count *plus* the sum of citation counts of every paper that cites it:

$$C_{\text{connected}}(p) = C(p) + \sum_{q \in \text{citers}(p)} C(q). \quad (8)$$

This second-order measure captures how influential the *citers* of a paper are. A paper cited by other heavily-cited papers propagates its conceptual footprint far more widely through the literature and thus through any corpus derived from it—than a paper cited only by obscure works.

Both measures serve as proxies for *corpus embeddedness*: the more a paper's ideas permeate the broader literature, the more redundant and distributed its representation is likely to be in the model's weights, and the harder it becomes to confine unlearning to a single, targeted forget set.

To examine whether citation counts differ systematically between the two groups, we plot, for each algorithm and forget-set configuration, the distribution of both normal and connected citation counts for papers affected *only* by the single active forget set (labelled SINGLE) against papers affected by *both* forget sets (labelled OVERLAPPED). Each distribution is rendered as a KDE-smoothed curve (outliers removed via the IQR fence method with $k = 1.5$ prior to plotting), with vertical lines indicating the group mean (dark green) and median (dark purple). Separate plots are produced for normal citation counts and connected citation counts for each of the six algorithm–configuration pairs, yielding twelve figures in total from Figure 8a to Figure 13b.

Across the plots, a consistent trend emerges: **papers that are forgotten by both forget sets tend to exhibit lower citation counts**—both normal and connected—than papers that are forgotten only by the forget set used during unlearning. This holds across most algorithm–configuration pairs, where the median citation value of the non-overlapped paper set lies to the right of the overlapped paper set (Figure 8a, 8b, 10a, 10b, 11a, 12a, 12b, 13a, 13b).

The implication is consistent with our proxy hypothesis: papers with lower citation counts are less deeply rooted in the pretraining corpus. Their knowledge is likely represented through fewer direct and derivative textual contexts, making the corresponding model representations less redundant and therefore easier to perturb. When unlearning is applied to one forget set, the update can spill over to the other forget set because both sets rely on a comparatively fragile and weakly reinforced representation of the same paper. By contrast, highly cited papers—and papers whose citers are themselves highly cited—leave a broader imprint on pretraining corpora. Their claims are represented not only directly but also indirectly through a large

web of derivative literature, making them more resistant to cross-set forgetting from a single unlearning signal.

This finding suggests that low-citation papers are more vulnerable to broad spillover across paraphrased forget sets, whereas highly cited papers may require stronger or more comprehensive unlearning signals to remove claim-level knowledge beyond the specific surface forms used during training.

O Use of AI Assistance

AI-based writing tools were used only for basic assistance during manuscript preparation, such as refining language after the initial text was written, improving grammar, and checking clarity. All core ideas, experimental design, dataset construction, analysis, and conclusions were developed and verified by the authors. The authors take full responsibility for the final content of the paper.