

---

# RippleBench: Capturing Ripple Effects by Leveraging Existing Knowledge Repositories

---

**Anonymous Author(s)**

Affiliation

Address

email

## Abstract

1 The ability to make targeted updates to models, whether for unlearning, debiasing,  
2 model editing, or safety alignment, is central to AI safety. While these interventions  
3 aim to modify specific knowledge (e.g., removing virology content), their  
4 effects often propagate to related but unintended areas (e.g., allergies). Due to  
5 lack of standardized tools, existing evaluations typically compare performance on  
6 targeted versus unrelated general tasks, overlooking this broader collateral impact  
7 called the “ripple effect”. We introduce RippleBench, a benchmark for systematically  
8 measuring how interventions affect semantically related knowledge. Using  
9 RippleBench, built on top of a Wikipedia-RAG pipeline for generating multiple-  
10 choice questions, we evaluate eight state-of-the-art unlearning methods. We find  
11 that all methods exhibit non-trivial accuracy drops on topics increasingly distant  
12 from the unlearned knowledge, each with distinct propagation profiles. We release  
13 our codebase for on-the-fly ripple evaluation as well as RippleBench-WMDP-Bio,  
14 a dataset derived from WMDP biology, containing 9,888 unique topics and 49,247  
15 questions.

## 16 1 Introduction

17 AI safety methods often seek to modify models’ knowledge, whether to unlearn harmful behaviors,  
18 update facts, or debias outputs, but such interventions rarely remain isolated. Edits can spill over  
19 to semantically relevant concepts and even those that are seemingly unrelated, this behaviour was  
20 termed as “ripple effect” [1]. As noted in [2], even when specific capabilities (e.g., chemical synthesis  
21 pathways or cybersecurity exploits) are removed, models can reconstruct them by recombining  
22 fragments of benign knowledge. This stems from the compositional, interconnected nature of large  
23 models: complex concepts are built from simpler components that often serve innocuous purposes, a  
24 phenomenon sometimes described as “dual use.” Consequently, attempts to fully “unlearn” harmful  
25 capabilities may also degrade otherwise safe information.

26 Standard evaluations of unlearning, model editing, or debiasing typically adopt a binary split between  
27 the forget set (concepts to erase or edit) and the retain set (everything else) [3]. This framing overlooks  
28 the continuum of semantic relationships, for example, the gradation between “bird flu” and “weapons  
29 of mass destruction.” While prior work has highlighted the need to consider related knowledge [4],  
30 comprehensive benchmarks for capturing these ripple effects are lacking.

31 We introduce RippleBench, a pipeline for systematically measuring the broader impact of targeted  
32 interventions. By leveraging knowledge repositories to generate multiple-choice questions across a  
33 spectrum of semantic proximity, RippleBench quantifies model performance not only on directly  
34 unlearned information but also on neighboring concepts, offering insight into when interventions  
35 cannot be treated independently.

36 We use RippleBench to develop a benchmark for unlearning, RippleBench-WMDP-Bio, which we  
37 use to evaluate eight popular unlearning methods applied to Llama3-8b-Instruct to unlearn dual-use  
38 biology knowledge from the WMDP-Bio benchmark. While prior reports [5] show minimal utility  
39 loss on unrelated benchmarks such as MMLU [6], we find consistent non-trivial degradation on  
40 semantically distant topics, with most methods showing gradual decay as distance increases.  
41 Finally, we release our code and a Wikipedia-RAG pipeline for generating ripple-effect evaluations  
42 on arbitrary topics. We hope RippleBench enables more rigorous, topic-specific assessment of  
43 ripple effects, fostering broader evaluation of unlearning and knowledge-editing methods. We also  
44 release RippleBench-WMDP-Bio on Huggingface.

## 45 2 Related Work

46 **Datasets and benchmarks.** The two most widely used benchmarks for unlearning are the Weapons  
47 of Mass Destruction Proxy (WMDP) [7] and the Task of Fictitious Unlearning (TOFU) [8]. WMDP  
48 tests models’ ability to generate content about hazardous topics in biosecurity, cybersecurity, and  
49 chemical security. TOFU provides synthetic data about fictitious authors, where the goal is to unlearn  
50 subsets of these authors while retaining generic knowledge. However, both benchmarks are limited:  
51 WMDP focuses narrowly on safety-critical topics, while TOFU evaluates only one synthetic task.  
52 Neither captures fine-grained collateral effects across a broad range of concepts.

53 **Unlearning methods.** The primary approach to mitigating harmful behaviors in models has been to  
54 teach refusal through fine-tuning ([9, 10, 11, 12]). This method, while effective in many scenarios,  
55 trains the model to avoid certain outputs but does not necessarily remove the underlying capability. In  
56 contrast, machine unlearning aims to selectively erase knowledge from models ([2, 13]). Approaches  
57 include fine-tuning to induce forgetting [14, 15, 16, 17, 18] and mechanistic interventions that directly  
58 ablate concepts [19, 20, 21, 22]. Recent work by [5] systematically compared eight unlearning  
59 methods against eleven attack strategies, releasing 64 checkpoints that we leverage for evaluation.

60 **Ripple effects.** Editing knowledge in LLMs can produce unintended propagation, known as the ripple  
61 effect [1]. Because knowledge is stored in interconnected representations, changing one fact (e.g.,  
62 “Canberra is Australia’s capital”) requires consistent updates to related facts. Failure to do so often  
63 yields contradictions and degraded multi-hop reasoning. Similar ripple effects appear in unlearning:  
64 removing unsafe concepts (e.g., “WMDP bio threat”) can inadvertently degrade performance on  
65 benign, related concepts (e.g., “biology”) [7, 23].

## 66 3 Method

67 Traditional evaluation of unlearning methods often relies on synthetic or limited test sets that fail  
68 to capture the full spectrum of a model’s knowledge. To address this limitation, we ground our  
69 evaluation in factual information extracted from authoritative sources by creating a pipeline to  
70 automatically generate test sets from individual facts taken from Wikipedia. By leveraging Wikipedia  
71 as a comprehensive knowledge repository, we can systematically evaluate a model’s understanding  
72 across diverse topics and varying semantic distances from the unlearning target. Furthermore, this  
73 pipeline circumvents the need to manually craft evaluation questions for the topic of interest and  
74 other semantically relevant concepts, thus scaling to thousands of topics and hundreds of thousands  
75 of questions while maintaining quality and consistency.

### 76 3.1 Benchmark Generation via Wikipedia

77 To efficiently navigate Wikipedia’s vast knowledge repository and identify semantically related  
78 topics, we developed Wiki-RAG (Wikipedia Retrieval-Augmented Generation), a specialized retrieval  
79 system optimized for semantic neighbor discovery. Wiki-RAG combines dense retrieval with efficient  
80 indexing to enable rapid identification of related topics across millions of Wikipedia articles. The  
81 pipeline consists of the following parts:

82 **Topic Extraction:** We start by mapping questions from source materials, such as a question about  
83 “the mechanism of anthrax toxin production” from the WMDP dataset, to topics, such as “Bacillus  
84 anthracis” with a large language model. This extraction process must balance specificity (to maintain  
85 precision in retrieval) with generality (to ensure adequate coverage in Wikipedia). We then map these  
86 target topics to relevant Wikipedia articles.

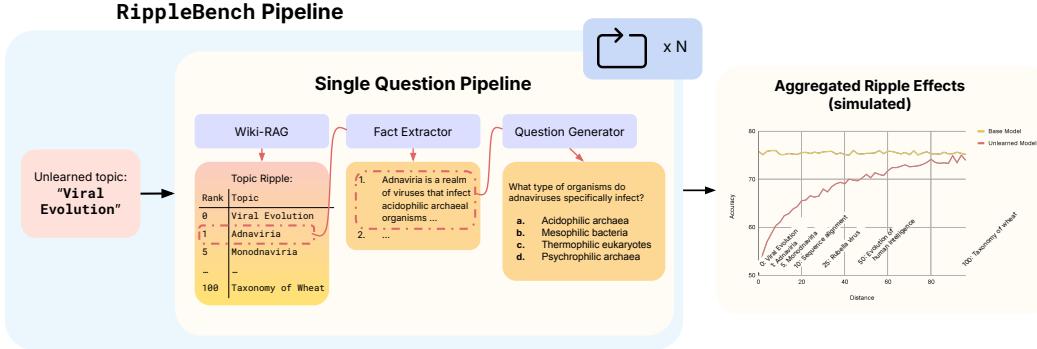


Figure 1: The RippleBench pipeline. Starting from an unlearned topic (e.g., *Viral Evolution*), Wiki-RAG retrieves related topics, factual statements are extracted, and language models generate multiple-choice questions. While we focus on WMDP-Bio in this work, the pipeline applies to any model-editing or unlearning task.

87 **Semantic Expansion:** Using a FAISS index [24] containing dense semantic embeddings produced  
 88 by SentenceTransformers for over 10 million Wikipedia articles, our Wiki-RAG system retrieves  
 89 topics spanning a spectrum of semantic similarity to the originals, capturing both closely and distantly  
 90 related knowledge. Wiki-RAG’s architecture is specifically designed to support the iterative expansion  
 91 process required for RippleBench generation, where each topic serves as a seed for discovering  
 92 additional neighbors.

93 **Fact and Question Generation:** For each topic, we extract key factual statements and employ  
 94 language models to convert these into multiple-choice questions with plausible distractors.

95 This process creates a scalable, up-to-date benchmark that can assess ripple effects for arbitrary topics  
 96 and unlearning interventions.

### 97 3.2 Quantifying Ripple Effects

98 Central to measuring ripple effects is the notion of *semantic distance* between the unlearned knowl-  
 99 edge and potentially affected information. We define this distance using a topic’s rank within a  
 100 Wikipedia-based RAG system. To build intuition, we provide an empirical example of this ranking  
 101 function in Section A.1. By evaluating model accuracy across questions at varying distances from the  
 102 unlearning target, we can assess both intended and unintended knowledge changes.

103 This distance metric serves three purposes: (1) it organizes evaluation topics along a continuum from  
 104 directly targeted to unrelated, (2) it enables quantitative analysis of how unlearning effects decay with  
 105 distance, and (3) it supports controlled experiments that measure the relationship between semantic  
 106 proximity and unlearning impact.

## 107 4 Experiments

108 We apply the RippleBench pipeline to construct **RippleBench-WMDP-Bio**, an evaluation set derived  
 109 from WMDP-Bio. Our experiments measure how unlearning harmful knowledge about biological  
 110 and chemical agents impacts performance on related topics at varying semantic distances.

### 111 4.1 Experimental Setup

112 **Unlearning Methods and Model.** We use Llama3-8b-Instruct [25], a fine-tuned version of Llama  
 113 3 optimized for helpful assistant behavior. We evaluate eight approaches: Gradient Difference  
 114 (GradDiff) [26], Random Misdirection for Unlearning (RMU) [27], RMU with Latent Adversarial  
 115 Training (RMU+LAT) [16], Representation Noising (RepNoise) [18], Erasure of Language Memory  
 116 (ELM) [28], Representation Rerouting (RR) [15], Tamper Attack Resistance (TAR) [17], and PullBack  
 117 & project (PB&J) [29].

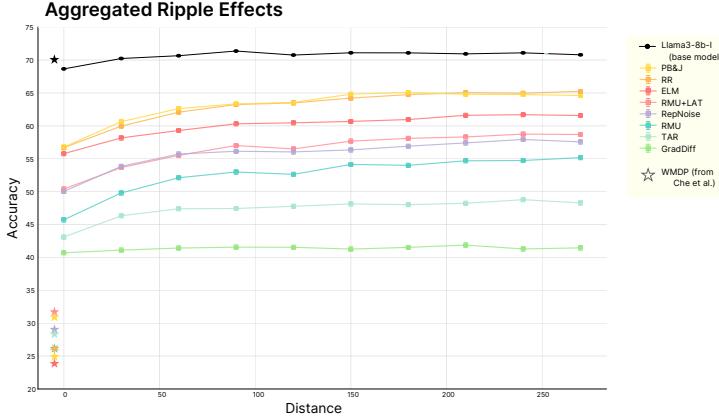


Figure 2: Ripple effects of unlearning methods on model performance across semantic distances. The base model (black) maintains consistently high accuracy, while unlearning methods show varying degrees of collateral degradation. ELM exhibits a smooth recovery with distance, whereas methods like TAR and GradDiff cause steep and persistent drops across all distances.

118 **Evaluation.** Models are evaluated on the full RippleBench dataset of 229,648 questions across 46,351  
 119 topics. When multiple unlearned questions map to the same higher-level topic (e.g., *Vaccines* and  
 120 *Anthrax* under *Biology*), regenerated items can yield near-duplicates. A deduplicated version contains  
 121 9,888 topics and 49,247 questions.<sup>1</sup>

## 122 4.2 Main Results: The Ripple Effect

123 Figure 2 shows how performance varies across semantic distances. As a sanity check, the base model,  
 124 Llama3, maintains consistently high accuracy, while unlearning methods display clear ripple effects,  
 125 impacting nearby topics. In this evaluation, no method came out clearly ahead, as methods generally  
 126 tradeoff better unlearning on WMDP against a stronger ripple effect (i.e., more effect on topics  
 127 semantically further from the unlearned dataset).

128 At the directly unlearned topics (distance 0), GRADDIFF and TAR show the steepest drops (over 25%  
 129 below baseline), with measurable degradation persisting well beyond distance 50. These patterns  
 130 highlight the importance of evaluating collateral effects when designing unlearning strategies.

131 We also see that reported unlearned accuracies on WMDP-Bio, as shown by the stars on the left-hand  
 132 side of Figure 2, differ significantly from accuracies on similar questions (distance 0 on RippleBench-  
 133 WMDP-Bio). This highlights that the evaluated unlearning methods do not generalize beyond the  
 134 distribution of questions in WMDP-Bio to the actual underlying topics.

## 135 5 Conclusion

136 We introduced **RippleBench**, a general-purpose evaluation framework, together with **RippleBench-WMDP-Bio**,  
 137 a dataset of 9,888 unique topics across 49,247 unique questions for measuring ripple  
 138 effects in machine unlearning. Our analysis shows that current unlearning methods often create sharp  
 139 discontinuities rather than smooth gradients, where unlearning is more strongly correlated with the  
 140 binary “Is WMDP Topic” label rather than with any continuous notion of semantic distance.

141 This reveals two challenges: defining semantic distance in a way that aligns with model behavior,  
 142 and designing methods that prevent blunt collateral damage to related concepts. By combining  
 143 a systematic evaluation pipeline with a Wikipedia-RAG infrastructure, RippleBench provides a  
 144 foundation for developing unlearning techniques that achieve precise, predictable forgetting while  
 145 mitigating unintended ripple effects.

<sup>1</sup>Dataset size is reduced by natural filtering: starting from 1,273 WMDP questions, we extracted 586 unique topics after deduplication. Further attrition occurred during fact extraction, where topics with insufficient Wikipedia content or API failures were excluded.

146 **References**

147 [1] Roi Cohen, Eden Biran, Ori Yoran, Amir Globerson, and Mor Geva. Evaluating the ripple  
148 effects of knowledge editing in language models, 2023.

149 [2] Fazl Barez, Tingchen Fu, Ameya Prabhu, Stephen Casper, Amartya Sanyal, Adel Bibi, Aidan  
150 O’Gara, Robert Kirk, Ben Bucknall, Tim Fist, et al. Open problems in machine unlearning for  
151 ai safety. *arXiv preprint arXiv:2501.04952*, 2025.

152 [3] Eleni Triantafillou, Peter Kairouz, Fabian Pedregosa, Jamie Hayes, Meghdad Kurmanji, Kairan  
153 Zhao, Vincent Dumoulin, Julio Jacques Junior, Ioannis Mitliagkas, Jun Wan, Lisheng Sun  
154 Hosoya, Sergio Escalera, Gintare Karolina Dziugaite, Peter Triantafillou, and Isabelle Guyon.  
155 Are we making progress in unlearning? findings from the first neurips unlearning competition,  
156 2024.

157 [4] Aengus Lynch, Phillip Guo, Aidan Ewart, Stephen Casper, and Dylan Hadfield-Menell. Eight  
158 methods to evaluate robust unlearning in llms. *arXiv preprint arXiv:2402.16835*, 2024.

159 [5] Zora Che, Stephen Casper, Robert Kirk, Anirudh Satheesh, Stewart Slocum, Lev E McKinney,  
160 Rohit Gandikota, Aidan Ewart, Domenic Rosati, Zichu Wu, et al. Model tampering attacks  
161 enable more rigorous evaluations of llm capabilities. *arXiv preprint arXiv:2502.05209*, 2025.

162 [6] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and  
163 Jacob Steinhardt. Measuring massive multitask language understanding, 2021.

164 [7] Nathaniel Li, Alexander Patel, Elham Sidani, Maheshan Sooriyabandara, Melody Wen, Cameron  
165 Allan, Silas Watts, Shrimai Gupte, Evan Smith, Kiera Kelley, et al. The wmdp benchmark:  
166 Measuring and reducing malicious use with unlearning. *arXiv preprint arXiv:2403.03218*, 2024.

167 [8] Pratyush Maini, Zhili Feng, Avi Schwarzschild, Zachary C Lipton, and J Zico Kolter. Tofu: A  
168 task of fictitious unlearning for llms. *arXiv preprint arXiv:2401.06121*, 2024.

169 [9] Mantas Mazeika, Long Phan, Xuwang Yin, Andy Zou, Zifan Wang, Norman Mu, Elham  
170 Sakhaee, Nathaniel Li, Steven Basart, Bo Li, et al. Harmbench: A standardized evaluation  
171 framework for automated red teaming and robust refusal. *arXiv preprint arXiv:2402.04249*,  
172 2024.

173 [10] Fan Liu, Zhao Xu, and Hao Liu. Adversarial tuning: Defending against jailbreak attacks for  
174 llms. *arXiv preprint arXiv:2406.06622*, 2024.

175 [11] Lei Yu, Virginie Do, Karen Hambardzumyan, and Nicola Cancedda. Robust llm safeguarding  
176 via refusal feature adversarial training. *arXiv preprint arXiv:2409.20089*, 2024.

177 [12] Stephen Casper, Lennart Schulze, Oam Patel, and Dylan Hadfield-Menell. Defending against  
178 unforeseen failure modes with latent adversarial training. *arXiv preprint arXiv:2403.05030*,  
179 2024.

180 [13] Sijia Liu, Yuanshun Yao, Jinghan Jia, Stephen Casper, Nathalie Baracaldo, Peter Hase, Yuguang  
181 Yao, Chris Yuhao Liu, Xiaojun Xu, Hang Li, et al. Rethinking machine unlearning for large  
182 language models. *Nature Machine Intelligence*, pages 1–14, 2025.

183 [14] Ronen Eldan and Mark Russinovich. Who’s harry potter? approximate unlearning in llms. *URL*  
184 <https://arxiv.org/abs/2310.02238>, 1(2):8, 2023.

185 [15] Andy Zou, Long Phan, Justin Wang, Derek Duenas, Maxwell Lin, Maksym Andriushchenko,  
186 J Zico Kolter, Matt Fredrikson, and Dan Hendrycks. Improving alignment and robustness with  
187 circuit breakers. *Advances in Neural Information Processing Systems*, 37:83345–83373, 2024.

188 [16] Abhay Sheshadri, Aidan Ewart, Phillip Guo, Aengus Lynch, Cindy Wu, Vivek Hebbar, Henry  
189 Sleight, Asa Cooper Stickland, Ethan Perez, Dylan Hadfield-Menell, et al. Latent adver-  
190 sarial training improves robustness to persistent harmful behaviors in llms. *arXiv preprint*  
191 *arXiv:2407.15549*, 2024.

192 [17] Rishub Tamirisa, Bhrugu Bharathi, Long Phan, Andy Zhou, Alice Gatti, Tarun Suresh, Maxwell  
 193 Lin, Justin Wang, Rowan Wang, Ron Arel, et al. Tamper-resistant safeguards for open-weight  
 194 llms. *URL <https://arxiv.org/abs/2408.00761>*, 2024.

195 [18] Domenic Rosati, Jan Wehner, Kai Williams, Lukasz Bartoszcze, David Atanasov, Robie Gonza-  
 196 les, Subhabrata Majumdar, Carsten Maple, Hassan Sajjad, and Frank Rudzicz. Representation  
 197 noising effectively prevents harmful fine-tuning on llms. *CoRR*, 2024.

198 [19] Phillip Guo, Aaquib Syed, Abhay Sheshadri, Aidan Ewart, and Gintare Karolina Dziugaite.  
 199 Mechanistic unlearning: Robust knowledge unlearning and editing via mechanistic localization.  
 200 *arXiv preprint arXiv:2410.12949*, 2024.

201 [20] Stefan Schoepf, Michael Curtis Mozer, Nicole Elyse Mitchell, Alexandra Brintrup, Georgios  
 202 Kaassis, Peter Kairouz, and Eleni Triantafillou. Redirection for erasing memory (rem): Towards  
 203 a universal unlearning method for corrupted data. *arXiv preprint arXiv:2505.17730*, 2025.

204 [21] Aashiq Muhamed, Jacopo Bonato, Mona T Diab, and Virginia Smith. Saes can improve  
 205 unlearning: Dynamic sparse autoencoder guardrails for precision unlearning in llms. In *ICML  
 2025 Workshop on Reliable and Responsible Foundation Models*, 2025.

207 [22] Xu Wang, Zihao Li, Benyou Wang, Yan Hu, and Difan Zou. Model unlearning via sparse  
 208 autoencoder subspace guided projections. *arXiv preprint arXiv:2505.24428*, 2025.

209 [23] Rohit Gandikota, Sheridan Feucht, Samuel Marks, and David Bau. Erasing conceptual knowl-  
 210 edge from language models. *arXiv preprint arXiv:2410.02760*, 2024.

211 [24] Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvassy, Pierre-  
 212 Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. The faiss library. 2024.

213 [25] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ah-  
 214 mad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, Amy Yang, Angela  
 215 Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem  
 216 Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson,  
 217 Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux,  
 218 Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret,  
 219 Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius,  
 220 Daniel Song, Danielle Pintz, Danny Livshits, Danny Wyatt, David Esiobu, Dhruv Choudhary,  
 221 Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab  
 222 AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Francisco  
 223 Guzmán, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Govind  
 224 Thattai, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah  
 225 Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan  
 226 Misra, Ivan Evtimov, Jack Zhang, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason  
 227 Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya  
 228 Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton,  
 229 Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Va-  
 230 suden Alwala, Karthik Prasad, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield,  
 231 Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Kushal  
 232 Lakhotia, Lauren Rantala-Yearly, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz  
 233 Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke  
 234 de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin  
 235 Kardas, Maria Tsimpoukelli, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kam-  
 236 badur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi,  
 237 Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Ning Zhang, Olivier Duchenne,  
 238 Onur Çelebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal  
 239 Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao  
 240 Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert  
 241 Stojnic, Roberta Raileanu, Rohan Maheswari, Rohit Girdhar, Rohit Patel, Romain Sauvestre,  
 242 Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hos-  
 243 seini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov,  
 244 Shaoliang Nie, Sharan Narang, Sharath Raparthy, Sheng Shen, Shengye Wan, Shruti Bhosale,  
 245 Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane

246 Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha,  
247 Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal  
248 Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet,  
249 Virginie Do, Vish Vogeti, Vitor Albiero, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin  
250 Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaofang Wang, Xiaoqing Ellen Tan,  
251 Xide Xia, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine  
252 Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert,  
253 Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aayushi Srivastava, Abha Jain,  
254 Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay  
255 Menon, Ajay Sharma, Alex Boesenberg, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit  
256 Sangani, Amos Teo, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu,  
257 Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Dong, Annie Franco,  
258 Anuj Goyal, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe,  
259 Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang,  
260 Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock,  
261 Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker,  
262 Carly Burton, Catalina Mejia, Ce Liu, Changhan Wang, Changkyu Kim, Chao Zhou, Chester  
263 Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Cynthia Gao, Damon  
264 Civin, Dana Beaty, Daniel Kreymer, Daniel Li, David Adkins, David Xu, Davide Testuggine,  
265 Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin  
266 Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn,  
267 Emily Wood, Eric-Tuan Le, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers,  
268 Fei Sun, Felix Kreuk, Feng Tian, Filippos Kokkinos, Firat Ozgenel, Francesco Caggioni, Frank  
269 Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee,  
270 Gil Halpern, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hakan  
271 Inan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison  
272 Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Hongyuan Zhan, Ibrahim Damlaj,  
273 Igor Molybog, Igor Tufanov, Ilias Leontiadis, Irina-Elena Veliche, Itai Gat, Jake Weissman,  
274 James Geboski, James Kohli, Janice Lam, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff  
275 Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin,  
276 Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh  
277 Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Kartikay Khandelwal, Katayoun  
278 Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kiran Jagadeesh,  
279 Kun Huang, Kunal Chawla, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro  
280 Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt,  
281 Madian Khabsa, Manav Avalani, Manish Bhatt, Martynas Mankus, Matan Hasson, Matthew  
282 Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Miao  
283 Liu, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel  
284 Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat,  
285 Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White,  
286 Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikhil Mehta, Nikolay Pavlovich  
287 Laptev, Ning Dong, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem  
288 Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager,  
289 Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang,  
290 Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghotham Murthy, Raghu Nayani, Rahul Mitra,  
291 Rangaprabhu Parthasarathy, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Russ  
292 Howes, Ruty Rinott, Sachin Mehta, Sachin Siby, Sai Jayesh Bondu, Samyak Datta, Sara Chugh,  
293 Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Mahajan, Saurabh Verma,  
294 Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Sheng Feng, Shenghao  
295 Lin, Shengxin Cindy Zha, Shishir Patil, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang,  
296 Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen  
297 Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Summer Deng,  
298 Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez,  
299 Tamar Glaser, Tamara Best, Thilo Koehler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim  
300 Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez,  
301 Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu  
302 Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Con-  
303 stable, Xiaocheng Tang, Xiaoqian Wu, Xiaolan Wang, Xilun Wu, Xinbo Gao, Yaniv Kleinman,  
304 Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin

305 Nam, Yu, Wang, Yu Zhao, Yuchen Hao, Yundi Qian, Yunlu Li, Yuzi He, Zach Rait, Zachary  
 306 DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, Zhiwei Zhao, and Zhiyu Ma. The llama 3  
 307 herd of models, 2024.

308 [26] Bo Liu, Qiang Liu, and Peter Stone. Continual learning and private unlearning. In *Conference*  
 309 *on Lifelong Learning Agents*, pages 243–254. PMLR, 2022.

310 [27] Nathaniel Li, Alexander Pan, Anjali Gopal, Summer Yue, Daniel Berrios, Alice Gatti, Justin D  
 311 Li, Ann-Kathrin Dombrowski, Shashwat Goel, Long Phan, et al. The wmdp benchmark:  
 312 Measuring and reducing malicious use with unlearning. *arXiv preprint arXiv:2403.03218*, 2024.

313 [28] Rohit Gandikota, Sheridan Feucht, Samuel Marks, and David Bau. Erasing conceptual knowl-  
 314 edge from language models. *arXiv preprint arXiv:2410.02760*, 2024.

315 [29] Anonymous. Unlearning in large language models via activation projections. 2025.

316 [30] Phillip Li, Huiwen Li, and Alexander Patel. Representation misdirection for unlearning. *arXiv*  
 317 *preprint arXiv:2404.03233*, 2024.

318 [31] Lev E McKinney, Anvith Thudi, Juhan Bae, Tara Rezaei Kheirkhah, Nicolas Papernot, Sheila A  
 319 McIlraith, and Roger Baker Grosse. Gauss-newton unlearning for the llm era. In *ICML 2025*  
 320 *Workshop on Machine Unlearning for Generative AI*, 2025.

## 321 A Supplementary Material

322 The unlearning methods evaluated by Che et al. (2025) can be broadly categorized based on their  
 323 underlying mechanism. Below, we briefly summarize each technique as described in their work.

324 **Gradient and Loss-Based Fine-Tuning** These methods adapt the standard fine-tuning process by  
 325 modifying the loss function to de-emphasize or penalize unwanted knowledge.

- 326 • **Gradient Difference (GradDiff):** Inspired by [26], this approach trains the model to  
 327 maximize the difference between the loss on the data to be forgotten and the loss on data to  
 328 be retained.
- 329 • **Representation Noising (RepNoise):** Proposed by [18], this method adds a noise-inducing  
 330 loss term. It encourages the model’s internal representations for harmful inputs to match a  
 331 simple Gaussian noise distribution.
- 332 • **Erasure of Language Memory (ELM):** Introduced by [23], ELM trains a model to mimic  
 333 the behavior of an “unknowledgeable” model on the target domain, effectively erasing the  
 334 specific concepts.

335 **Representation and Activation Manipulation** These techniques intervene more directly on the  
 336 model’s internal activations to suppress or redirect information flow related to the unwanted concepts.

- 337 • **Random Misdirection for Unlearning (RMU):** From [30], this technique involves pertur-  
 338 ing model activations for harmful inputs while explicitly preserving activations for benign  
 339 ones.
- 340 • **RMU with Latent Adversarial Training (RMU+LAT):** An extension by [16], this method  
 341 strengthens RMU by using adversarial attacks in the latent space during training on the  
 342 forget set.
- 343 • **Representation Rerouting (RR):** Also known as “circuit breaking” ([15]), this technique  
 344 trains the model to map latent states associated with unwanted topics to orthogonal, unrelated  
 345 representations.
- 346 • **K-FAC for Distribution Erasure (K-FADE):** This approach from [31] learns a set of  
 347 projections in the activation space that maximally degrade performance on the forget set  
 348 while minimally impacting a broader retain distribution.

349 **Meta-Learning for Robustness** This category focuses on training the model to be inherently  
350 resistant to tampering attacks.

351 • **Tamper Attack Resistance (TAR):** Proposed by [17], TAR is a meta-learning approach that  
352 preemptively trains a model to be robust against a fine-tuning adversary, making it harder to  
353 undo the unlearning.

354 **A.1 Translating RAG Scores into Semantic Distance**

355 To operationalize semantic distance, we rely on RAG rank. In this section we aim to build some  
356 intuition for how RAG ranks are constructed from underlying cosine similarity scores between  
357 Wikipedia article embeddings retrieved by Wiki-RAG. Figure 3 illustrates this process for the seed  
358 topic *Anthrax*. High-scoring neighbors such as *Anthrax weaponization* or *Bacilli* appear at low  
359 ranks, indicating close semantic proximity. As rank increases, retrieved topics gradually become less  
360 relevant (e.g., *Lobar pneumonia*) before eventually diverging to unrelated entries (e.g., *List update*  
361 *problem*, *List of years in politics*). This curve highlights the long tail of retrieval and motivates  
362 our bucketization of distances: low ranks capture tightly connected knowledge, while higher ranks  
363 provide semantically distant or noisy contexts.

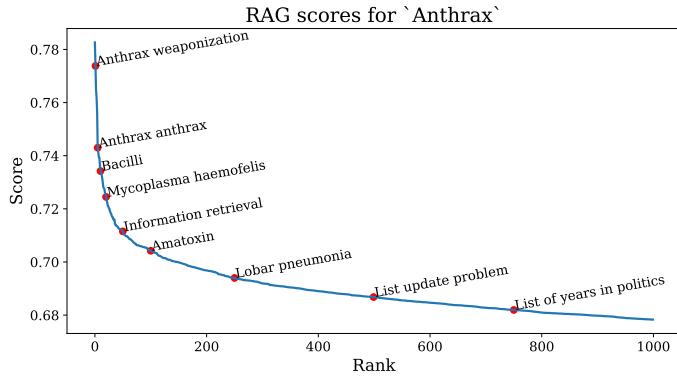


Figure 3: Example of RAG similarity scores for the seed topic *Anthrax*. Closely related neighbors (left) receive high similarity scores, while more distant or irrelevant topics (right) appear at lower scores and higher ranks. This mapping provides intuition for how semantic distance is defined and bucketized in RippleBench.