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IN-CONTEXT UNLEARNING: LANGUAGE MODELS AS FEW SHOT UNLEARNERS

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ABSTRACT

Machine unlearning, the study of efficiently removing the impact of specific training points on the trained model, has garnered increased attention of late, driven by the need to comply with privacy regulations like the *Right to be Forgotten*. Although unlearning is particularly relevant for LLMs in light of the copyright issues they raise, achieving precise unlearning is computationally infeasible for very large models. To this end, recent work has proposed several algorithms which approximate the removal of training data without retraining the model. These algorithms crucially rely on access to the model parameters in order to update them, an assumption that may not hold in practice due to computational constraints or when the LLM is accessed via API. In this work, we propose a new class of unlearning methods for LLMs we call "In-Context Unlearning", providing inputs in context and without having to update model parameters. To unlearn a particular training instance, we provide the instance alongside a flipped label and additional correctly labelled instances which are prepended as inputs to the LLM at inference time. Our experimental results demonstrate that these contexts effectively remove specific information from the training set while maintaining performance levels that are competitive with (or in some cases exceed) state-of-the-art unlearning methods that require access to the LLM parameters.

1 Introduction

Over the past decade predictive models developed via machine learning (ML) algorithms have become ubiquitous in high-stakes decision making settings including hiring, criminal justice, and credit scoring. While regulation governing responsible use of algorithms remains nascent, several regulatory principles have been adopted to specifically safeguard user privacy [33, 43], one of which is called the *Right to be Forgotten*. The Right to be Forgotten offers users more control over their personal data, by giving them the ability to submit a deletion request retracting permission for a company to utilize their personal data at any given time – even if for example, the company has already trained a ML algorithm using it [3, 18, 33, 43]. This raises a real dilemma for tech platforms who want to comply with the spirit of the regulation and avoid possibly breaking the law [44], on how exactly this data should be "removed" from any models trained on the data. A second motivation comes from an orthogonal concern to privacy: copyright infringement. Generative models like LLMs can often regurgitate their training data verbatim or with only superficial changes, leading to credible claims of copyright infringement when the underlying data is itself protected by copyright. When a copyrighted output of a model is generated, the model owner may then be required to "take down" the copyrighted work from the model. A safe way to resolve these dilemmas would be to fully retrain the predictive model any time an instance in its training set was removed due to a deletion request, but as a recent paper from Stanford on copyright issues in generative models [21] remarks: *Unlearning is a nascent research area and retraining a model without a taken down datapoint could be exceedingly costly [...] But new research is needed to identify new and improved mechanisms for handling takedown requests in this relatively new setting.*

Work in "Machine Unlearning" seeks to bridge the gap by building algorithms that remove the influence of the deleted point from a trained model, while avoiding the computationally expensive step of fully re-training on the updated dataset [13, 16, 22, 38].

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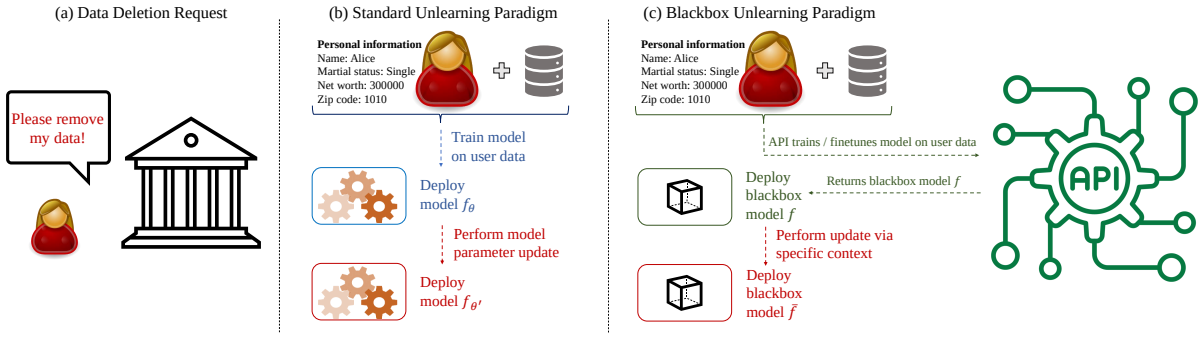


Figure 1: Comparing the standard unlearning paradigm in panel (b) with the blackbox unlearning paradigm in panel (c). In the conventional approach, the model owner, having control over the training of the deployed model, adjusts its parameters in response to deletion requests. On the other hand, in the blackbox paradigm, data is channeled to an API which yields a blackbox model. To adhere to deletion requests, the model owner must either completely retrain the model through the API or employ in-context unlearning to meet the deletion request.

At the same time as ML privacy regulation has started to gain traction, the release of Large Language Models (LLMs) has marked a pivotal transition in machine learning research [6]. Modern LLMs have demonstrated competency in a vast array of challenging tasks, ranging from language comprehension [36], reasoning [7] to tabular data generation [4]. These models not only exhibit effective abilities on tasks they were designed for, but they also display remarkable adaptability to unfamiliar tasks. This surprising versatility is partially attributed to a learning paradigm called "in-context learning" [6], wherein the model has access to a set of in-context examples, a minimal collection of input and label pairs, that are added to the prompt at inference time to enhance the performance of LLMs.

Despite the prominence of LLMs, and extensive recent work on machine unlearning, studying unlearning in LLMs is relatively unexplored [25]. Perhaps this is because compared to conventional machine unlearning on image classifiers for example, unlearning in LLMs has two additional challenges. First, many LLMs operate as black-boxes particularly when they are deployed through "ML as a Service" platforms (see Figure 1).[3] As a result, standard unlearning techniques that operate via gradient descent on the model's parameters cannot be implemented [31]. Second, even if the unlearning algorithm has "white-box" access (access to model parameters), running gradient descent on LLMs with many billions of parameters as in [25] might be computationally infeasible.

To address these challenges, we propose a novel class of unlearning methods suitable for large language models. To the best of our knowledge, this work is the first to suggest In-Context UnLearning (`ICUL`) which deploys a uniquely built context to eliminate the influence of a training point on the model output. In order to unlearn a particular training instance, the model context is constructed in a way where both the training point and its reversed label are provided at the beginning of the context alongside additional correctly classified context examples sampled from the training data distribution (see Figure 2). Our `ICUL` method does not require any knowledge of the LLM's parameters, and yet manages to maintain performance levels that are competitive with or in some cases exceed the state-of-the-art LLM unlearning method that requires access to the LLM parameters and the computation of costly gradient steps [25].

We experiment with multiple established real world datasets such as Yelp reviews, SST-2, and Amazon reviews to evaluate the effectiveness of our proposed unlearning method. Our experimental results on text classification tasks clearly demonstrate the efficacy of the proposed unlearning method, and highlight that it practically eliminates a training point's influence on the model output. These results indicate the significant potential for unlearning training points in a black-box style just through the model's forward pass. Our proposed methods and findings offer a new perspective on unlearning mechanisms in LLMs:

- **New unlearning paradigm for LLMs**: This is the first work to use in-context learning for machine unlearning by specifically constructing contexts that induce model behavior that is indistinguishable from the behavior of a re-trained model.
- **Black-box removal mechanism**: `ICUL` works in a black-box fashion and does not require parameter access. This makes it a useful tool to patch a model until the model's updated or retrained version can be deployed at the next deployment phase. Thus it is complementary to existing white-box unlearning techniques with higher computational burdens.

[3]For example, OpenAI offers a fine-tuning service for some of their proprietary GPT models: `openai.com/blog/gpt-3-5-turbo-fine-tuning-and-api-updates`.

- **Competitive model performance**: Our empirical results show that given access to an in-context unlearned LLM, an external auditor cannot reliably distinguish between held out test points and training points that were subsequently unlearned from the model. Furthermore, the in-context unlearned model has performance on unseen test points that is competitive with state-of-the-art unlearning methods for LLMs which require access to model parameters.

2 Related Work

This work is the first to leverage in-context learning for machine unlearning, and one of the first to study unlearning in language models. Below we discuss related work for each of these topics.

In-Context Learning. Transformers form the foundation of contemporary LLM architectures. The reason behind their remarkable achievements is thought to involve a concept called "in-context learning" (ICL) [6, 11, 27]. This refers to their ability to adapt to new tasks flexibly by incorporating data provided in the context of the input sequence itself, rather than fine-tuning which explicitly updates weights. Exploring the full capabilities of ICL remains an active area of research, with recent works trying to understand its potential better empirically by studying in-context example design [12, 26, 27, 29]. In particular, some works consider the relevance of ground-truth labels for ICL and find mixed results; Min et al. [29] find that ground-truth labels have little impact on performance while the findings by Wei et al. [46] suggest that only language models with larger scale can adopt their predictions to align with flipped label contexts. Another line of research studies (supervised) in-context learning theoretically [1, 2, 28, 30, 35, 45, 48, 50]. Initially, Garg et al. [12] empirically showed that linear transformers can learn simple function classes like linear regressors in-context. Inspired by these observations, Von Oswald et al. [45] puts forth a weight construction for trained transformers that implements a single step of gradient descent in a forward pass, which has subsequently been studied in more detail showing that the corresponding weight construction is globally optimal [1, 28, 50] and that gradient flow reaches this optimum [50]. While all these works study how learning can be facilitated through in-context examples, none of these works explore how unlearning can be achieved by designing in-context examples.

Machine Unlearning. Motivated by GDPR's "Right to be Forgotten" recent literature develops procedures for updating machine learning models to remove the impact of training on a subset of points without having to retrain the entire model from scratch [13, 15, 16, 22, 23, 25, 31, 38, 47]. These works can be divided categorically into two sections: exact unlearning approaches that redesign training in order to permit efficient re-training (e.g., Ginart et al. [13], Sekhari et al. [38]) and approximate unlearning which merely approximates retraining (e.g., Jang et al. [25], Neel et al. [31]). The latter approach has been likened to "forgetting" [19, 24, 41] which tracks whether machine learning models progressively unlearn samples during the course of training and is typically quantitatively assessed by *membership inference attack* (MIA) accuracy [24]. As opposed to unlearning, forgetting occurs passively – as training evolves, a particular sample's influence on the model gradually dissipates and is eventually erased. To quantify forgetting, [24] implements `LiRA`, the state-of-the-art MIA proposed in [8], that approximates the optimal likelihood ratio based test via sample splitting and training of shadow models. In Section 3.2 we adopt `LiRA` to empirically evaluate unlearning; to the best of our knowledge we are the first to use MIA attacks to empirically assess unlearning in LLMs. Prior research has explored approximate machine unlearning on discriminative classifiers, generally image classifiers (e.g., Goel et al. [14], Golatkar et al. [15]), where the aim often is to forget entire classes like "cats" or "ships". Approximate unlearning approaches typically update the model by taking gradient ascent steps on the deleted points [31], or are tailored to specific hypothesis classes such as linear regression [10, 20, 23] or kernel methods [49].

Contribution. Since re-training in LLMs is infeasible, approximate unlearning techniques are the only ones that are relevant to LLMs. To the best of our knowledge, the only paper on approximate unlearning in LLMs is due to Jang et al. [25] who suggest to use gradient ascent on the deleted points [31]. Relative to these works, our work stands out as the first to investigate unlearning tokens for language models (LMs) in a black-box fashion. We refer to our approach as "in-context unlearning" since our focus is on forgetting specific knowledge represented by the tokens at inference time by providing contexts that mimic the effect of re-training, offering a fundamentally novel perspective on the topic.

3 Preliminaries

Here, we first discuss the generic formulations of in-context learning. We then discuss how to measure unlearning success empirically.

3.1 In-Context Learning

In-context learning has recently emerged as a new paradigm that allows auto-regressive language models to learn tasks using a few examples in the form of context demonstrations [6]. Here, we follow common practice [6, 11, 27], and

consider the following definition of in-context learning: For a given pretrained language model f_θ, a set of context demonstrations D_{context} and a query input, the language model generates a sequence of tokens with a predefined length. For example, when the model is used for text classification, it typically outputs one additional token as its prediction from a set of C possible tokens where C is usually large (e.g., for the Bloom model $C = 250680$). The context D_{context} consists of an optional task instruction and s demonstration examples; therefore, D_{context} = {[Instruction input]$_0$ [Example input 1]$_1$[Label 1]$_1$, ... [Example input s]$_s$[Label s]$_s$}. The prompt, which uses D_{context} along with the query [Query Input]$_{s+1}$, is then provided as input for the language model prediction. In-context learning has emerged as a way to improve a pretrained model's predictions without the need of costly finetuning the model for a specific task. As such it is usually used to improve model predictions, and not in a way to remove information from a trained model.

3.2 Measuring Approximate Machine Unlearning

We now define how we measure (approximate) unlearning. Our unlearning notion is that of [5, 13, 31], but adapts the metric of membership inference attack success to operationalize this definition [14, 17]. Let $S \subset \mathcal{S}^*$ denote the training set, sampled from a distribution $\mathcal{D} \in \Delta(\mathcal{S})$. Let $\mathcal{T} : \mathcal{S}^* \to \Theta$ be the (randomized) training algorithm that maps S to a parameterized model $f_{\theta(S)}$. Further define the forget set as the subset of points to be forgotten from the trained machine learning model denoted by $S_f \subset S$. We define an unlearning procedure $\mathcal{U}$ that takes as input the model $f_{\theta(S)}$, the forget set S_f of data samples that should be deleted, and the train set S (and possibly some auxiliary information which we suppress), and outputs an updated model $\bar{f} \sim \mathcal{U}(f_{\theta(S)}, S, S_f)$. Denote the probability law of the training algorithm on input S by p_S, the law of the exact re-training algorithm by $p_{S\setminus S_f}$, and the law of the unlearning algorithm by $p_{\mathcal{U}}$. As first formalized in [13], the goal of an approximate unlearning algorithm is to produce $p_{\mathcal{U}} \approx p_{S\setminus S_f}$, or equivalently where $d(p_{S\setminus S_f}, p_{\mathcal{U}})$ is small for some distance measure between distributions d. Empirically verifying whether $d(p_{S\setminus S_f}, p_{\mathcal{U}})$ is small is difficult for two reasons: i) For computational reasons we do not have direct access to samples from $p_{S\setminus S_f}$, and ii) even if we did these distributions are extremely high dimensional and so we cannot compare them efficiently.

We address issue (i) by approximating the re-training distribution via sample-splitting (described in more detail in Appendix C); by training multiple models on splits of the data that do not contain S_f, we can approximate samples from $p_{S\setminus S_f}$. This approach is known as training "shadow-models" and has been employed for membership inference in [8, 39]. We address (ii) by re-formulating the problem of bounding $d(p_{\mathcal{U}}, p_{S\setminus S_f})$ as a hypothesis testing problem. Le Cam's Lemma (see Theorem 2.2 in [42]) establishes a correspondence between $d(p_{\mathcal{U}}, p_{S\setminus S_f})$ and the ability of an optimal hypothesis test to distinguish $p_{\mathcal{U}}$ from $p_{S\setminus S_f}$ based on a single sample. More specifically, we imagine a model f is sampled from $p_{\mathcal{U}}$ with probability $1/2$ else from $p_{\mathcal{U}}$ with probability $1/2$, and conduct a hypothesis test to determine which distribution f was sampled from:

$$\mathrm{H}_0 : f \sim p_{S\setminus S_f} \text{ vs. } \mathrm{H}_1 : f \sim p_{\mathcal{U}}. \tag{1}$$

Rejecting the null hypothesis corresponds to inferring that f was not from the re-training distribution. The Neyman-Pearson lemma [32] asserts that the optimal hypothesis test at a predetermined false-positive rate involves thresholding the likelihood-ratio test Λ:

$$\Lambda = \frac{p_{\mathcal{U}}(f)}{p_{S\setminus S_f}(f)}. \tag{2}$$

As discussed, approximating Equation 2 is intractable due to the high dimensionality of f, and so we follow recent work on MIAs, that instead takes the likelihood ratio with respect to the distribution of losses on the forget points S_f for both models. This is closely related to the `LiRa` attack statistic proposed in [8], but differs critically in that the numerator considers the model produced by training on S_f *and then unlearning* via $\mathcal{U}$ rather than the model that results after training. When then define the `LiRA-Forget` statistic $\hat{\Lambda}$:

$$\hat{\Lambda} = \frac{\prod_{(\mathbf{x},\mathbf{y})\in S_f} p_{\mathcal{U}}\big(\ell(f(\mathbf{x}), \mathbf{y})\big)}{\prod_{(\mathbf{x},\mathbf{y})\in S_f} p_{S\setminus S_f}\big(\ell(f(\mathbf{x}), \mathbf{y})\big)}, \tag{3}$$

where ℓ denotes an appropriate loss function. As in these recent works we approximate the univariate distributions on losses in the numerator and denominator of (3) via sample-splitting. Specifically we fine-tune models on sub-sampled datasetes that either contain or do not contain S_f. To approximate the numerator, on the datasets that do contain S_f, we run $\mathcal{U}$ to unlearn S_f, and then compute the updated model's loss on S_f. To approximate the denominator, we simple take the models that were not trained on S_f and compute their losses on S_f. As in [8] we model the logit of the model's confidence as normal, and use these transformed confidences to estimate the likelihood ratio. Further details are provided in Appendix C.

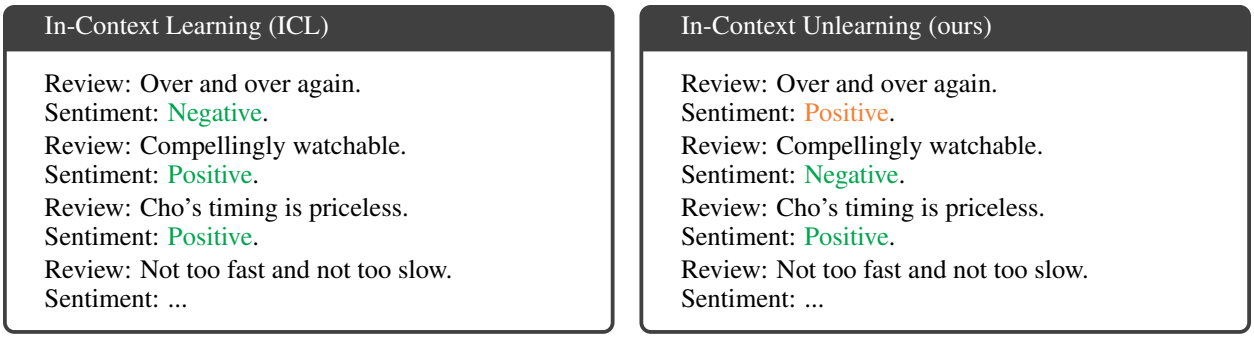


Figure 2: **Comparing in-context learning with in-context unlearning**. **Left**: Standard in-context learning provides labeled examples from the data distribution $\mathcal{D}$ in the context to make a prediction. **Right**: In-context unlearning removes the influence that samples from the forget set S_f have on the query completion by providing examples from the forget set with opposite labels (e.g., for "Over and over again." the label was flipped from Negative to Positive).

We have described how to compute our unlearning success statistic $\hat{\Lambda}$, but it remains to discuss what values of $\hat{\Lambda}$ should be considered "successful". We continue our analogy to recent work in evaluating membership inference attacks, and follow the paradigm introduced in [8] that focusing on true positive rates (in this case of predicting that the loss came from the unlearned model) at low false positive rates as the most intuitive measure of MIA attack success. In addition to plotting the full log-log ROC curves (Figures 3a and 3b) we also report the AUC. Unlike in the MIA context, where a successful attack has an AUC $\gg .5$, and an ROC curve that is above the diagonal even at very low FPRs, in our setting a successful unlearning algorithm corresponds to the failure of the LRT, and so we hope to see ROC curves that are very close to the diagonal even at low FPRs.

4 Our Framework: In-Context Unlearning

In this section, we describe our framework called In-Context Unlearning (`ICUL`) in more detail. For a given LLM, we finetune the model on the specific classification dataset using the following template for each sample: *"*[*Input*] [*Label*]*"*. We finetune using the standard causal language loss which encourages the model to predict the next token correctly given a total vocabulary of C possible tokens, where C is usually large (e.g., for the Bloom model $C = 250680$).

4.1 In-Context Unlearning

Recall that the main goal of our framework is to eliminate the need to re-finetune the model from scratch or to update the parameters of the model when unlearning a specific training data point. Instead, at inference time, we construct a specific context which lets the language model classify text as if it had never seen the specific data point during training before. To this end, our framework leverages incorrectly and correctly labelled examples to construct the following prompt which is provided as input to the LLM at inference time. More specifically, we suggest the following 3 step prompt construction approach which we term `ICUL`:

1. **Step:** **Flip label on forget point.** Given a deletion request, we flip the label on the corresponding training point whose influence should be removed from the model resulting in the template: *"*[*Forget Input*]$_0$ [*Flipped Label*]$_0$*"*.

2. **Step:** **Add s correctly labelled training points.** Next, excluding the forget point, we randomly sample s labeled example pairs which we add to the template of step 1, resulting in the updated template: *"*[*Forget Input*]$_0$ [*Flipped Label*]$_0$ \n [*Input 1*]$_1$ [*Label 1*]$_1$ \n $\cdots$ [*Input s*]$_s$ [*Label s*]$_s$*"*.

3. **Step:** **Prediction.** Finally, we add the query input to the template resulting in the final prompt *"*[*Forget Input*]$_0$ [*Flipped Label*]$_0$ \n [*Input 1*]$_1$ [*Label 1*]$_1$ \n $\cdots$ [*Input s*]$_s$ [*Label s*]$_s$ [*Query Input*]$_{s+1}$*"* and let the model predict the next token using temperature $t = 0$.

The above procedure captures the following intuition: The label flipping operation in Step 1 aims to remove the influence a specific training point has on the model outcome. Since Step 1 may cause the model to "overcorrect" on the forget point leading to decreased test accuracy and unlearning, Step 2 serves as an efficient way to reduce the effect of the label flipping, which the number of points s allows us to trade-off.

4.2 Additional Considerations for In-Context Unlearning

To tease apart the different factors that contribute to successful in-context unlearning, we conduct additional analyses where we vary the `ICUL` prompt construction above.

Varying context length. One key factor to consider is how the length of the context s influences the unlearning process. We run experiments that vary the total number of correctly labelled context examples $s \in \{2, 4, 6\}$, which we refer to as `ICUL(s)`.

ICL baseline. We also investigate the necessity of label flipping for successful `ICUL`, in order to rule out the hypothesis that our observed unlearning is a result of appending the correctly labeled examples in-context. In all of our experiments we include the baseline where we do not flip the label on the point to be unlearned in Step 1, resulting in the following prompt: *"*$[\textit{Forget Input}]_0$ $[\textit{Label}]_0$ $\backslash n$ $[\textit{Input 1}]_1$ $[\textit{Label 1}]_1$ $\backslash n \cdots$ $[\textit{Input s}]_s$ $[\textit{Label s}]_s$ $[\textit{Query Input}]_{s+1}$*"*. We term this setting `ICL(s)` as it corresponds to standard in-context learning.

Dependence on forget point. The last key aspect to consider is whether `ICUL` requires dependence on the point to be forgotten. To analyze this aspect, the unlearning point from step 1 is substituted with a randomly selected training point paired with its reversed label, resulting in the subsequent prompt: *"*$[\textit{Random Train Input}]_0$ $[\textit{Flipped Label}]_0$ $\backslash n$ $[\textit{Input 1}]_1$ $[\textit{Label 1}]_1$ $\backslash n \cdots$ $[\textit{Input s}]_s$ $[\textit{Label s}]_s$ $[\textit{Query Input}]_{s+1}$*"*. We call this setting `Random ICUL(s)`.

5 Empirical Evaluation

We now present our empirical analysis. First, we empirically show that in-context unlearning is successful at unlearning information from a finetuned LLM in a forward pass – surprisingly `ICUL` unlearns more effectively than the white-box gradient ascent approaches, when evaluated via the likelihood ratio measures described in Section 3.2. In Section 5.2 we show that the unlearned model maintains extremely competitive model performance when using in-context unlearning. Finally, we run ablation experiments that confirm our method works as intended; namely it is not merely providing examples in contexts that results in the measured unlearning, it is the fact that we specifically flip the label of the point in question, and then pad the context with 2 to 6 examples with the correct label.

We first describe the real-world data sets we use in our experiments, the LLMs we evaluate on, and the benchmark unlearning methods we compare to.

Datasets. We evaluate our prompt constructions on 3 standard text classification tasks, Stanford Sentiment Treebank (SST2) [40], Amazon polarity, and Yelp polarity [51]. The SST2 dataset is derived from Rotten Tomatoes reviews [34] and the task is to predict whether a given sequence of text has a positive or negative sentiment. We also use Yelp and Amazon polarity datasets which were originally introduced by Zhang et al. [51]. The task is binary classification for whether a given review is positive (four or five stars) or negative (one or two stars). In line with work on auditing privacy leakages [9, 39], we randomly sub sampled smaller data sets of 25000 points from each of these datasets for finetuning. We show the average results over 10 runs for all of our experimental settings unless stated otherwise and usually report ± 1 standard deviation across these runs.

Large Language Models. We conduct experiments on Bloom large language models (560M, 1.1B) [37] which we finetune for one epoch using the standard causal language cross-entropy loss with initial learning rate set to $5 \cdot 10^{-5}$ for all the above datasets. At inference time, the models predict the next token from their 250680 dimensional vocabulary given a context and query.

Methods. We implement the only available baseline for unlearning in large language models suggested by Jang et al. [25]. The authors suggest to use gradient ascent on the forget set as an unlearning algorithm, which can be interpreted as maximizing instead of minimizing the loss on the forget points. We follow their suggestion and set the learning rate to $5 \cdot 10^{-5}$, use one epoch and do sequential unlearning where every point from the forget set is individually and sequentially unlearned using a constant learning rate schedule. Additionally, since a learning rate of $5 \cdot 10^{-5}$ usually led to poor results, we followed Jang et al. [25, Appendix] and did a search over different learning rates $\{5 \cdot 10^{-5}, 3 \cdot 10^{-5}, 1 \cdot 10^{-5}\}$. In the main text, we report the most competitive results only. Additional results on the hyperparameter search are shown in Figure 7 of Appendix B.

5.1 Evaluation Measures

When evaluating the efficacy of the unlearning method $\mathcal{U}$, two distinct but interrelated objectives emerge. The primary concern is to ascertain whether the unlearning process is valid, in that it eliminates the specific data point from the trained model, and secondarily whether it maintains performance (e.g. in terms of classification accuracy) after unlearning. We first discuss measures that gauge the validity of the unlearning process.

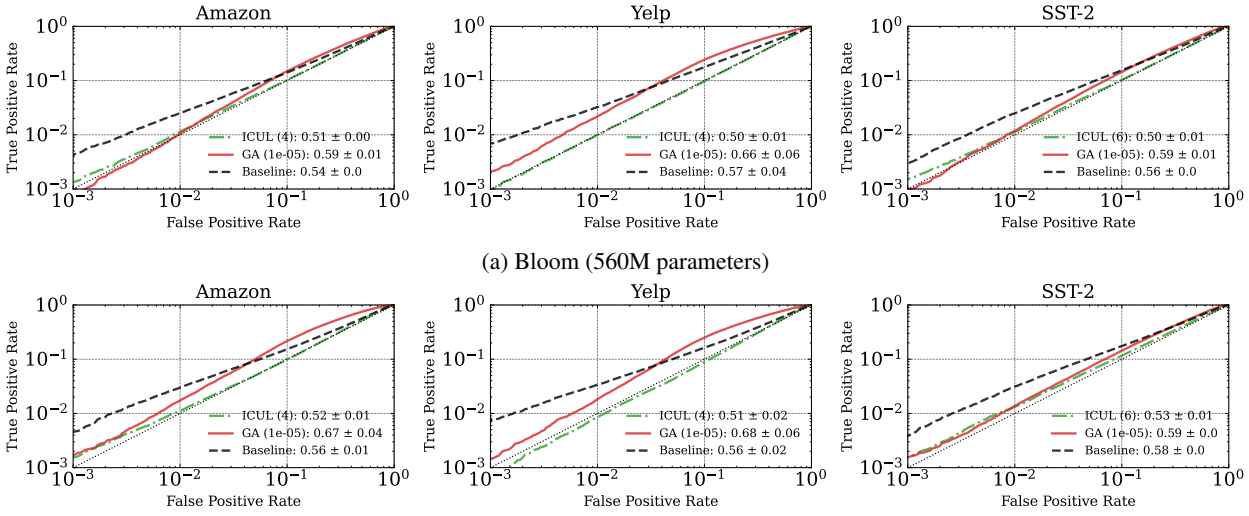
Compare train vs. held out samples on the initial model $f_{\theta(S)}$. This initial evaluation serves as a starting point of the privacy problem and the extent of information leakage from the model. If `LiRA` cannot differentiate between samples used for training and those held out for testing, it implies that the model has not leaked significant information. Furthermore, if distinguishing between training and held-out samples was already infeasible before unlearning was initiated, it becomes challenging to empirically argue that unlearning has achieved its intended purpose, as maintaining the status quo (i.e., doing nothing) would be a perfectly reasonable strategy for the model owner. To conduct this evaluation, we run the `LiRA` attack using 10 shadow models [8] on the model $f_{\theta(S)}$.

Compare forget vs. held out samples on the updated model $\bar{f}$**.** The key evaluation assesses the success of unlearning. Can the model effectively forget the specific data point in question? In other words, is the model output on a data point when it is held out of the training set indistinguishable from the output on the same data point when it was initially part of the model but subsequently removed through the unlearning process? This critical evaluation is conducted by running the `LiRA-Forget` attack discussed in Section 3 using 10 shadow models. In line with previous work on MIAs, to evaluate attack success we present receiver operating characteristic (ROC) area under the curve (AUC) scores [39]. Additionally, we follow Carlini et al. [8] and also provide logscaled ROC curves and the true positive rates (TPRs) of attacks at low false positive rates (FPRs) at or below 10^{-1} since, for MI attacks, average metrics such as AUC may be misleading. The core intuition is that if a MI attack can determine even a minuscule subset of the training data with exceptional confidence, the attack should be deemed successful. Therefore, we mainly report our results using this particular metric.

Evaluating model performance. In addition to these evaluations, the overall performance of the model is a crucial consideration [17]. The model's predictive capabilities should demonstrate effectiveness across various scenarios, including 1) train points S, 2) points S_f targeted for unlearning and 3) randomly drawn test points.

5.2 Evaluating the Efficacy of Unlearning

In this Section, we evaluate the efficacy of unlearning whose results are summarized in Figure 3 and Table 1. We compare `GA`, which has access to model parameters, with our proposed `ICUL` method, and compare their performance to two natural benchmarks.



(a) Bloom (560M parameters)

(b) Bloom (1.1B parameters)

Figure 3: **Comparing unlearning success across different unlearning methods for different datasets and model sizes using log scaled ROC curves.** The closer to the diagonal the better, which amounts to the adversary randomly guessing whether a given point is (still) part of the model or not. For the green and red curves, the MI attacks were run against the updated models $\bar{f}$, which were either updated using `GA` (solid red) or `ICUL` (dashdot green). The black dashed line represents the baseline performance of not removing the point where the same attack is run on the model $f_{\theta(S)}$, as described in Section 5.1. The numbers in brackets denote the best parameters and the numbers after that show the AUC ± 1 standard deviation across 10 evaluation runs. Shades indicate ± 1 standard deviation across 10 evaluation runs.

Dataset	Metric	Bloom 560M			Bloom 1.1B		
		Baseline	ICUL	GA	Baseline	ICUL	GA
Amazon	AUC	0.5420 ± 0.0040	**0.5060** ± 0.0049	0.5870 ± 0.0149	0.5570 ± 0.0090	**0.5220** ± 0.0108	0.6740 ± 0.0410
	$\text{TPR}_{.001}$	0.0043 ± 0.0016	0.0013 ± 0.0006	**0.0008** ± 0.0004	0.0046 ± 0.0011	**0.0015** ± 0.0008	0.0017 ± 0.0007
	$\text{TPR}_{.01}$	0.0251 ± 0.0028	0.0114 ± 0.0030	**0.0106** ± 0.0017	0.0300 ± 0.0019	**0.0112** ± 0.0037	0.0173 ± 0.0038
	$\text{TPR}_{.1}$	0.1403 ± 0.0046	**0.1028** ± 0.0141	0.1491 ± 0.0082	0.1536 ± 0.0124	**0.0986** ± 0.0161	0.2164 ± 0.0446
Yelp	AUC	0.5690 ± 0.0430	**0.5030** ± 0.0110	0.6590 ± 0.0584	0.5580 ± 0.0183	**0.5090** ± 0.0181	0.6790 ± 0.0552
	$\text{TPR}_{.001}$	0.0068 ± 0.0037	**0.0010** ± 0.0004	0.0021 ± 0.0012	0.0074 ± 0.0016	**0.0006** ± 0.0004	0.0014 ± 0.0006
	$\text{TPR}_{.01}$	0.0323 ± 0.0111	**0.0100** ± 0.0037	0.0219 ± 0.0095	0.0339 ± 0.0093	**0.0085** ± 0.0038	0.0182 ± 0.0054
	$\text{TPR}_{.1}$	0.1768 ± 0.0482	**0.0968** ± 0.0211	0.2423 ± 0.0820	0.1622 ± 0.0291	**0.0893** ± 0.0198	0.2507 ± 0.0750
SST-2	AUC	0.5610 ± 0.0030	**0.5050** ± 0.0067	0.5930 ± 0.0100	0.5840 ± 0.0049	**0.5300** ± 0.0077	0.5940 ± 0.0049
	$\text{TPR}_{.001}$	0.0030 ± 0.0010	0.0015 ± 0.0002	**0.0009** ± 0.0004	0.0039 ± 0.0008	**0.0016** ± 0.0007	**0.0016** ± 0.0003
	$\text{TPR}_{.01}$	0.0250 ± 0.0021	**0.0113** ± 0.0016	0.0118 ± 0.0013	0.0313 ± 0.0027	**0.0134** ± 0.0020	0.0137 ± 0.0010
	$\text{TPR}_{.1}$	0.1551 ± 0.0043	**0.1032** ± 0.0065	0.1441 ± 0.0067	0.1751 ± 0.0080	**0.1165** ± 0.0119	0.1436 ± 0.0065

Table 1: **Comparing unlearning success at or below false positive rates of 10^{-1} across unlearning methods.** We report TPR_x, which measures the TPR at FPR $= x$, for different datasets and model sizes. Additionally, we report AUC, which denotes the area under the receiver operating characteristic curve. The results are averaged over 10 evaluation runs and include ± 1 standard deviation.

Benchmarks. The first benchmark consists of the decision not to unlearn the point from the model, denoted as `Baseline` in all figures. The second benchmark is random guessing, represented by the dashed diagonal line across all figures indicating an equal ratio of FPR to TPR. An unlearning method should demonstrate performance below the `Baseline` and as close to the random guessing benchmark as possible in Figure 3, particularly for lower FPRs like $\{10^{-3}, 10^{-2}, 10^{-1}\}$.

Comparing `GA` and `ICUL`. Inspecting Figure 3, we find the `ICUL` curve, for all datasets and both model sizes, traces close to the diagonal that represents a random guess probability of whether a point intended for removal is still part of the model. It is also crucial to highlight that our method consistently surpasses the `Baseline` in terms of AUC and TPRs at FPRs on all datasets. When we contrast `ICUL` with `GA`, `ICUL` consistently achieves superior (lower) AUC scores. Furthermore, inspecting Table 1, `ICUL` bests `GA` in 6 out of 6 cases on the metric of TPRs at fixed FPR $= 0.1$, in 5 out of 6 cases at FPR $= 0.01$, and in 3 out of 6 cases at FPR $= 0.001$. These results show conclusively that `ICUL` greatly reduces the chance of identifying the forget point as part of the training set in way that is both (i) non-trivial and (ii) outperforms the existing `GA` approach despite only having black-box access to the model.

5.3 Evaluating the Unlearned Model's Performance

In this section, we assess the performance of the models post-unlearning, using accuracy as the evaluation metric. An overview of these results can be found in Table 2. With respect to the forget points' performance, given that the unlearning procedure $\mathcal{U}$ is intended to successfully delete these specific data points, the model's performance on these instances should mirror this removal. As anticipated, for both `GA` and `ICUL`, the performance on these forget points dips significantly below the training points' performance and mimics the test point performance more closely. Lastly,

Dataset	Method	Bloom 560M			Bloom 1.1B		
		Train	Forget	Test	Train	Forget	Test
Amazon	ICUL(4)	0.933 ± 0.012	**0.930** ± 0.012	0.918 ± 0.013	0.955 ± 0.007	**0.953** ± 0.010	0.939 ± 0.005
	GA(1e-05)	**0.959** ± 0.002	0.918 ± 0.012	**0.940** ± 0.002	**0.966** ± 0.001	0.920 ± 0.003	**0.948** ± 0.001
	Baseline	0.960 ± 0.002	0.960 ± 0.002	0.940 ± 0.002	0.967 ± 0.001	0.967 ± 0.001	0.949 ± 0.002
Yelp	ICUL(4)	0.942 ± 0.027	**0.940** ± 0.028	0.936 ± 0.015	0.964 ± 0.009	**0.962** ± 0.012	0.958 ± 0.006
	GA(1e-05)	**0.974** ± 0.001	**0.944** ± 0.010	**0.958** ± 0.003	**0.979** ± 0.001	0.947 ± 0.003	**0.966** ± 0.002
	Baseline	0.974 ± 0.001	0.974 ± 0.001	0.958 ± 0.003	0.980 ± 0.001	0.980 ± 0.001	0.966 ± 0.002
SST-2	ICUL(6)	0.870 ± 0.035	**0.856** ± 0.035	0.835 ± 0.030	0.925 ± 0.018	**0.903** ± 0.016	0.881 ± 0.015
	GA(1e-05)	**0.951** ± 0.004	0.845 ± 0.020	**0.909** ± 0.003	**0.965** ± 0.002	0.860 ± 0.007	**0.919** ± 0.002
	Baseline	0.953 ± 0.004	0.953 ± 0.004	0.911 ± 0.002	0.966 ± 0.002	0.966 ± 0.002	0.920 ± 0.002

Table 2: **Classification accuracy on train, forget and test points across all data sets and model sizes.** While `GA` always has more favorable test accuracy, the performance gap between `ICUL` and `GA` on test data becomes smaller as we increase model size.

the model should be able to effectively generalize beyond the training data. While `GA` consistently exhibits better test accuracy than `ICUL`, as we expand the model size, the performance gap between `ICUL` and `GA` on unseen test data

narrows down. Moreover, ICUL still obtains reasonable test accuracy on all datasets, particularly on the larger Bloom 1.1B model, where the test accuracy is within 1% of the performance of the baseline model on Amazon and Yelp.

5.4 Sensitivity Analysis: Towards Understanding In-Context Unlearning

Next, we study the factors in the context construction that lead to successful in-context unlearning, namely whether label-flipping on the forget point is necessary, whether the forget point needs to be the point with flipped label, and the impact of context length. These results are summarized in Figures 4 and 5.

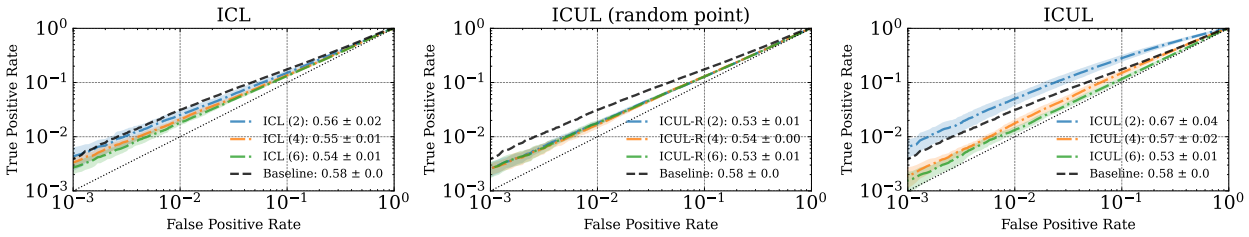
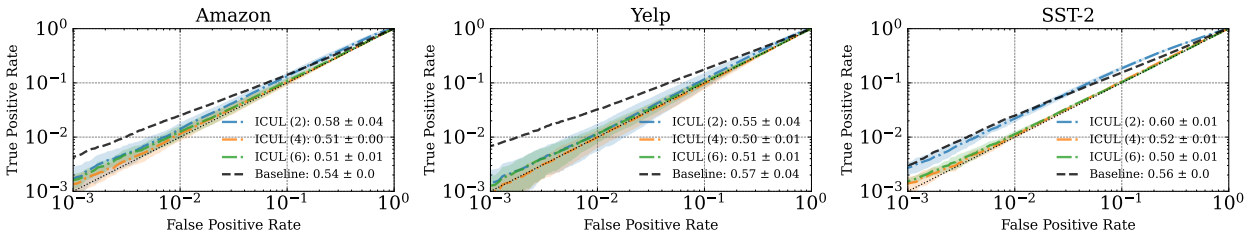
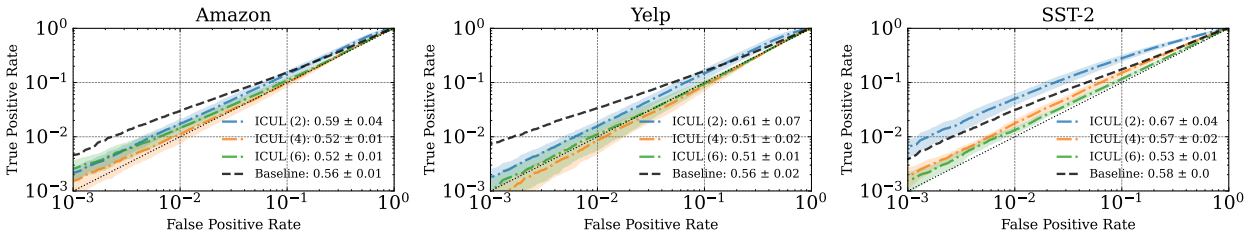


Figure 4: **Sensitivity analysis.** We plot MI attack performances as in Figure 3, this time across different context constructions described in Section 4.2 for the 1.1B Bloom model on the SST-2 dataset. The closer to the dotted diagonal the better.



(a) Bloom (560M parameters)

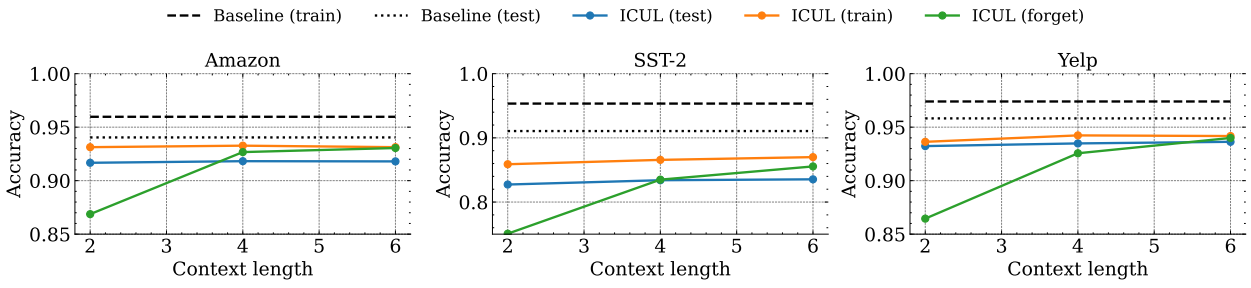


(b) Bloom (1.1B parameters)

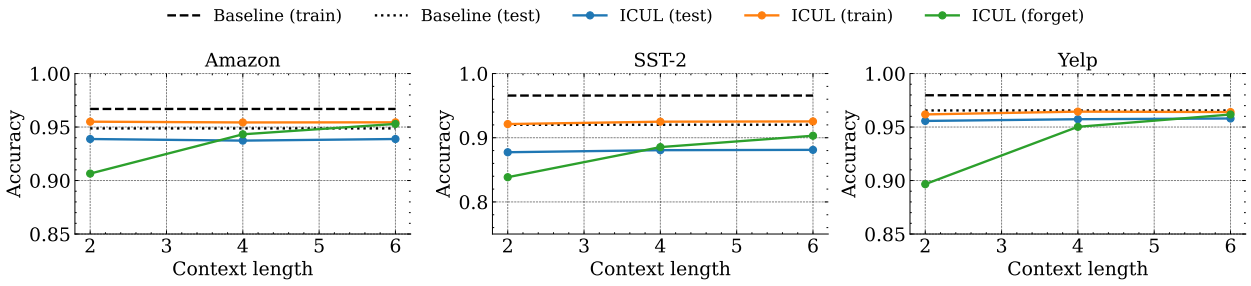
Figure 5: **Varying context length for** ICUL. Same setup as in Figure 3. We plot the MI attack performance using log scaled ROC curves across different datasets and model sizes. The MI attacks were run against the updated models f, which was updated using ICUL. The closer to the dotted diagonal the better.

ICL baseline. Here we empirically study the effect of label flipping on unlearning success. A comparison of the standard ICL approach (Figure 4, left), where the label of the point we aim to remove is kept unchanged, with our proposed ICUL method (Figure 4, right) illustrates that label flipping is a crucial factor that pushes the ICUL curve closer to the random guessing benchmark. This finding highlights the essential role of label flipping in successful unlearning and challenges recent studies that explore its significance in ICL [29, 46]. While these studies propose that only large-scale language models can modify their predictions, our results suggest that smaller LLMs can adjust their predictions to mimic an output distribution that has never encountered the point aimed for removal before.

Varying context length. For ICUL, changing the context length can significantly improve results in terms of unlearning success as seen in Figure 5. With shorter context lengths, such as 2, the reversed label of the forget point typically leaves an overly negative impact on the model's confidence scores. This generally results in poorer average performance than the Baseline, as shown by the comparison of their AUC scores (e.g., ICUL(2) scores at 0.67 while Baseline at 0.58). Furthermore, context lengths of this size are often not sufficient enough to reduce TPRs at FPR levels of



(a) Bloom (560M parameters)



(b) Bloom (1.1B parameters)

Figure 6: **Classification performance as we vary context length for** `ICUL`. We report classification accuracy on train, forget and test points across all data sets and model sizes. For better readability, ± 1 standard deviation was excluded.

$\{10^{-3}, 10^{-2}, 10^{-1}\}$ down to the level of random guessing benchmark. On the other hand, 4 or 6 additional context examples tend to yield the best performance.

In terms of model performance, the situation is more nuanced as can be seen from Figure 6. While the context length has clear impact on forget points, test points seem to be impacted very little by the number of context examples.

Dependence on forget point. Finally, we examine whether the point intended for deletion needs to be part of the prompt. Evidence supporting this requirement is displayed by comparing the middle and right plots in Figure 4. This comparison highlights that in the low FPR regime at or below 10^{-2}, our proposed `ICUL` method substantially surpasses the `ICUL` that uses a random point.

6 Conclusion

In this work, we presented a novel class of unlearning algorithms for LLMs that are able to unlearn even without access to the model parameters. Our method effectively creates a model output distribution that mimics the scenario where a particular point was never part of the model's training dataset. Our algorithm for `ICUL` creates prompts comprising the data point targeted for removal, its flipped label, as well as other accurately labeled instances, which are then provided as inputs to the LLM during inference. In order to evaluate our unlearning algorithm, we extend prior work on membership inference and measuring forgetting to empirically measure unlearning using a likelihood-ratio based test we call `LiRA-Forget`. Our empirical results suggest that `ICUL` reliably removes the influence of training points on the model since `LiRA-Forget` cannot reliably distinguish between held out points and training points that were subsequently unlearned from the model. Moreover, our empirical observations indicate that label flipping for in-context examples does have an impact on the model's output. This finding challenges earlier research that argued label flipping of in-context examples had an insignificant impact on smaller LLMs [29, 46]. Future research will seek to extend our methodology to larger datasets and models, while also exploring the potential of unlearning multiple points. Because of its practical appeal and the novelty of our approach, this work establishes an important new perspective on the field of machine unlearning.

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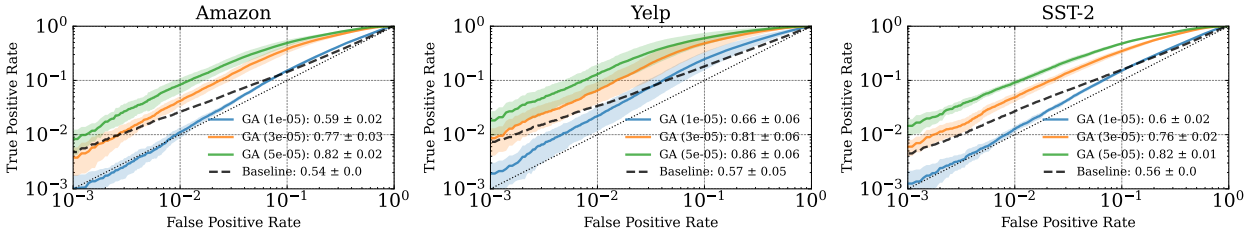
A Reproducibility

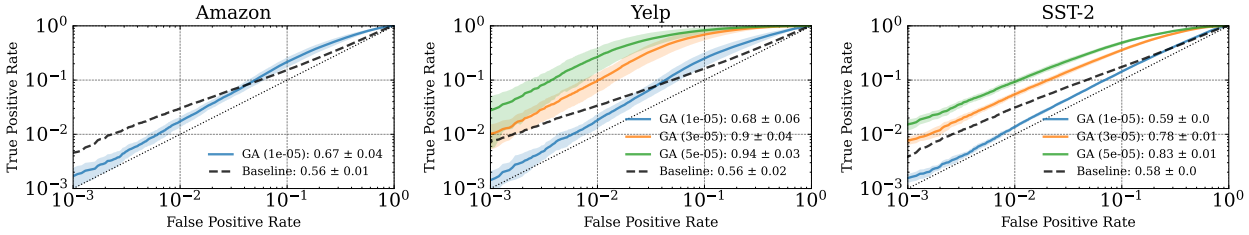
All experiments are run using Nvidia Tesla V100 GPUs. We finetuned 60 models across two different model sizes and 4 different data sets; 30 models were finetuned using Bloom560M and another 30 models were finetuned using Bloom 1.1B. On average, finetuning took approximately 1 hour per model, which makes for 60 GPU hours. Regarding the main experiments, we conducted unlearning using both GA and ICUL. First, for ICUL we ran inference across 3 context length configurations across 60 models and each run took 2 hours on average. This amount to 360 GPU hours. Second, for GA, the situation was very similar. Updating the models using GA across 3 learning rate configurations for all 60 models where each inference run took approximately 2 hours amounts to another 360 GPU hours. Finally, we ran the additional sensitivity experiments on SST-2 using Bloom 1.1B. These experiments were conducted for 10 models, using 3 context length configurations and 3 sensitivity setups, where each inference run took approximately 1.5 hours, which makes for a total of 135 GPU hours. In total, we used 855 GPU hours which approximately amounts to 36 GPU days. Note that these numbers include run times to find competitive learning rates and context lengths.

B Gradient Ascent Hyperparmeters

Vary the learning rate on `GA`. For `GA`, changing the learning rate can dramatically improve results, where smaller learning rates usually significantly improve results in terms of unlearning success and model performance as shown in Figures 7 and 8.



(a) Bloom (560M parameters)



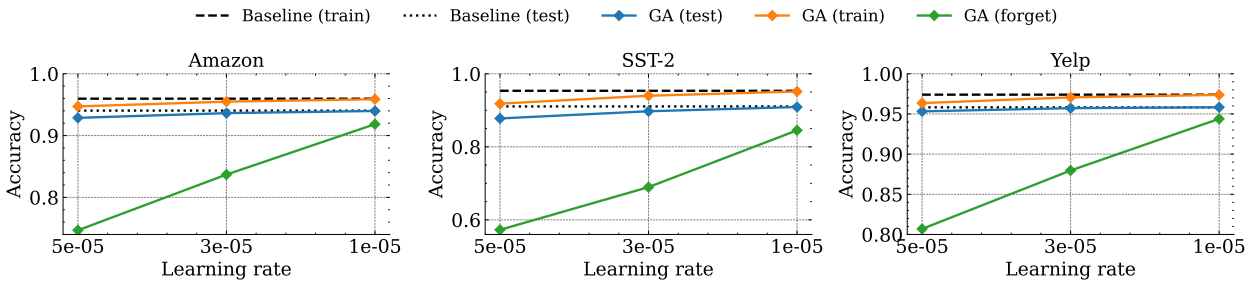
(b) Bloom (1.1B parameters)

Figure 7: **Varying the learning rate for `GA`.** We plot the MI attack performance using log scaled ROC curves across different datasets and model sizes. The MI attacks were run against the updated models $\bar{f}$, which was updated using `GA`. The closer to the diagonal, which amounts to the adversary randomly guessing whether a forget point is still part of the model or not, the better. The numbers in brackets denote the best parameters and the numbers after that show the AUC ± 1 standard deviation across 10 evaluation runs. The black dashed line represents the baseline performance of not removing the point where the same attack is run on the model $f_{\theta(S)}$, as described in Section 5.1. Shades indicate ± 1 standard deviation across 10 evaluation runs.

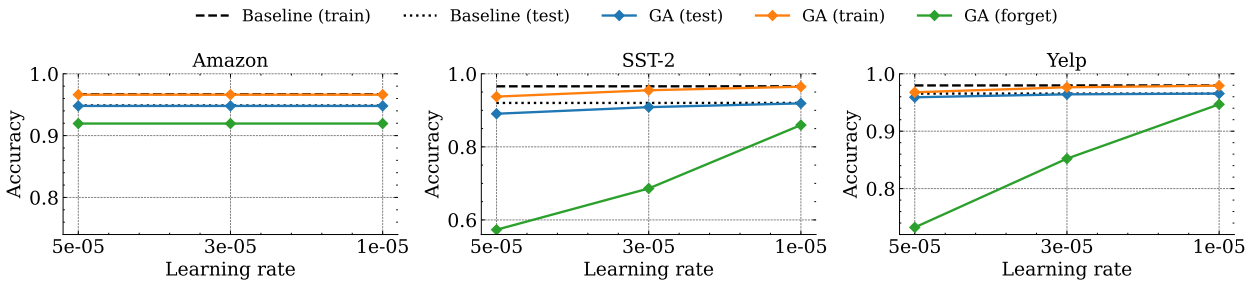
C Details on the Machine Unlearning Evaluation

Operationalizing the Likelihood-ratio Audit. Operationalizing the likelihood ratio test from (3) requires access to the distribution of losses under the null and alternative hypotheses. While analytical solutions are usually not available, we can readily get large samples from these two distributions. In an ideal scenario, this entails that we would need to fit as many re-train models and unlearned models as possible for every forget set of interest. Since this approach becomes computationally too burdensome, we use the following two-step approximation:

Approximating the distributions under H_0 and H_1. Here we adapt the sample splitting procedure first introduced by Carlini et al. [8] to forget sets with sizes J greater than 1. We train K shadow models on random samples from



(a) Bloom (560M parameters)



(b) Bloom (1.1B parameters)

Figure 8: **Classification performance as we vary the learning rate for** `GA`. We report classification accuracy on train, forget and test points across all data sets and model sizes. For better readability, ± 1 standard deviation was excluded from the figure.

the data distribution $\mathcal{D}$ so that a fraction p of these models are trained on the forget set $S_f = \{(\mathbf{x}_j, \mathbf{y}_j)\}_{j=1}^{J}$, and a fraction $(1-p)$ are not. In particular, we train shadow models on $K = 10$ subsets of $\mathcal{D}$ so that each forget set $S_f \in D$ appears in $K \cdot p$ subsets. This approach has the advantage that the same K shadow models can be used to estimate the likelihood-ratio test for all the forget sets. Finally, we fit the parameters of two Gaussian distributions to the confidence scores of the retain models and the unlearned models on S_f. Across all experiments, we use $p = 0.5$ and $J = 1$.

Model losses. Instead of using the actual losses, we follow Carlini et al. [8] and compute model confidences as $\phi(f(\mathbf{x}), \mathbf{y}) = \log(f(\mathbf{x})_y) - \log(\sum_{y'} f(\mathbf{x})_{y'})$ which the authors show yields the strongest empirical attack performance. This score compares the confidence the model assigns to the true class (e.g., 'positive') with the confidences the model assigns to all other classes (i.e., all other words from the approximately 250680 dimensional vocabulary). The higher the score is the more confident the model is in the correct prediction.